Empirical Studies on Efficiency, Economies of Density, and Productivity of Railroad Companies in Japan

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博　士　論　文

Empirical Studies on Efficiency, Economies of Density, and Productivity of Railroad Companies in Japan
（日本における鉄道事業者の効率性・密度の経済性・生産性に関する実証研究）

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Chapter 1

Introduction

1.1 Background

Regional small and medium-sized passenger railroad companies in Japan face operational difficulties due to decreasing numbers of passengers and high facility costs. As the birthrate in Japan continues to decline and the population ages, the population along the railroad routes has decreased. The decrease in passengers is compounded by greater levels of private car ownership. The aforementioned effects resulted in 75% of Japanese regional small and medium-sized passenger railroad companies being burdened with a deficit in FY 2011 (Kajimaya and Tokutake, 2013). The reduction in the number of passengers is one of the factors responsible for reducing railroad companies' productivity. Furthermore, facility costs accounted for about 45% of total costs in FY 2011 (Kajimaya and Tokutake, 2013). If railroad companies continue to operate inefficiently under such conditions, then supplying transport services will become increasingly difficult in future.

Part of the railroad companies' facility costs are fixed costs. With regard to the decreasing-cost industries such as the railroad industry, the fixed costs of companies are said to be high. In these industries, companies can reduce their average costs by increasing the output (e.g., the volume of transport services). However, this is not a feasible solution for small and medium-sized railroad companies because their numbers of passengers are decreasing. As such, one way to reduce their average costs and to improve their performance and long-term viability is to reduce their facilities (Tretheway et al., 1997). For example, by removing tracks or rolling stocks (train vehicles) that have not been used recently, they can reduce their fixed costs and improve their financial situation.

There are also other ways of reducing facility costs. For example, track improvements such as replacing light rails with heavier rails and wooden sleepers with concrete sleepers can reduce facility costs because doing so would reduce the frequency of track maintenance (Japan Railway Construction, Transport and Technology Agency, 2008a,b). Thus, track improvements can increase the productivity or ease the problem of reduced productivity and improve companies' performance and long-run viability, despite the reduced number of passengers. In fact, some small and medium-sized passenger railroad companies have begun upgrading their rails and sleepers. Although these improvements require a significant investment, the installation of heavy rails and concrete sleepers is subsidized by national and local governments. This eases the financial burden on railroad companies, which would otherwise need to fund the changes themselves.

1.2 Objectives and Significance of this Thesis

Based on the background described in the previous section, this thesis aims to determine which type of Japanese regional small and medium-sized passenger railroad companies operate inefficiently or face operational difficulties, and what these companies (and governments) can do to improve their performance and long-run viability. To achieve these objectives, we conduct several empirical studies, applying econometric methods to panel data on the sample of railroad companies. Achieving our objective will contribute to understanding the factors affecting the efficiency and fixed costs of Japanese small and medium-sized passenger railroad companies, the quantitative impact of track improvements on productivity, and the length of time needed between improving the tracks and seeing a change in productivity. Therefore, this study is significant from the perspectives of railroad companies' investment decisions and government policy.

1.3 Definitions and Interpretations of Concepts

To achieve our objectives, we conduct several empirical studies and analyses based on four economic concepts: technical efficiency (TE), economies of density (EOD), returns to density (RTD), and total factor productivity (TFP). In this section, we define and interpret each of these four concepts.

Farrell (1957) proposed the concept of TE. In order to grasp the concept of TE, we first explain technical *inefficiency*. According to Farrell (1957), (input-oriented) technical *inefficiency* measures the extent to which inputs can be reduced without changing the output quantity (Coelli et al., 2005). For example, in the railroad case, the output quantities are passenger kilometers (i.e., the number of passengers multiplied by the train vehicles' kilometrage) or vehicle kilometers (i.e., vehicles' kilometrage). More precisely, technical *inefficiency* is the proportion by which all inputs can be reduced without a reduction in output (Coelli et al., 2005). By considering technical *inefficiency* from the opposite point of view, we can now define TE. (Input-oriented) TE is the ratio of all *minimized* input quantities needed to produce the present quantity of output to the *actual* input quantities. The ratio takes a value of not more than unity (Farrell, 1957). If a company's TE is equal to unity, then it is technically efficient, implying that it cannot maintain its present quantity of output if it reduces its input quantities; in other words, the input quantities are minimized. If a company's TE is less than unity, then it is technically inefficient because it can maintain its level of output even though it reduces its input quantities; in other words, its input quantities are not minimized.

EOD describes the decrease in average costs when output increases, with the network size (e.g., distance of railway lines) held constant (Harris, 1977).

The existence or intensity of EOD is measured by the RTD. The RTD is the proportional increase in transport volume resulting from proportional increases in all inputs, holding the network size fixed (Caves et al., 1985; Smith et al., 2015). Specifically, the RTD indicates how much output increases when all inputs or total costs increase by 1%. If the RTD is greater than unity, then this is evidence of increasing RTD and, thus, EOD. Thus, we use the terms "EOD" and "increasing RTD" interchangeably (Caves et al., 1984). The presence of EOD (increasing RTD) means a company can achieve a large *increase in* transport volume with relatively small *additional* inputs or *total costs*. If the RTD is equal to unity, then we have constant RTD and, thus, no EOD. A constant RTD indicates that a company can increase its transport volume by the same proportion as it increases all inputs or total costs. If the RTD is less than unity, there is a decreasing RTD, and diseconomies of density. In this case, the company needs a large increase in *additional* inputs or *total costs* to achieve a small *increase in* transport volume. See section 3.2 for more detail, as well as an explanation of how EOD and the RTD are related to fixed costs.

TFP is the ratio of output to input volume, using an appropriate set of weights (e.g., output elasticity with respect to inputs) (Smith et al., 2015). A high TFP value means the company can achieve a large transport volume using a relatively small input. Conversely, a low TFP means the company needs a large input to achieve a relatively small transport volume.

1.4 Structure of this Thesis

This thesis is structured as follows.

In Chapter 2, we examine what type of railroad companies are operating in a technically (in)efficient manner. To do this, we estimate the input distance function and inefficiency function. The empirical results are as follows. First, railroad companies that transport passengers mainly over long distances are more technically efficient than those that focus on shorter distances. Second, railroad companies that mainly transport commuters are more technically efficient than those that transport more non-commuters, such as tourists. A possible reason for these results may be that longer distances per passenger mean a higher value of output. In addition, those railroad companies with a high ratio of rail-pass passengers transport a relatively stable number of passengers every year.

Chapter 3 investigates the fixed costs of railroad companies, as well as what type of railroad companies face high fixed costs. To do this, we estimate a variable cost system and predict the RTD of the railroad companies. The empirical findings are as follows. First, the fixed costs of railroad companies may be high. Second, the RTD of railroad companies that transport mainly non-commuting passengers are higher than those of railroad companies that transport mainly commuters. Because a high RTD means a high fixed cost, companies that transport mainly non-commuters may face higher fixed costs. Therefore, removing unused tracks or rolling stocks would improve companies' performance and long-run viability, especially in the case of companies that transport mainly non-commuters.

Chapter 4 examines how long it takes to increase (or ease the decrease in) the productivity of railroad companies after making track improvements, as well as the extent of the change in productivity in the long-run. Here, we estimate a production function, predict the TFP of the railroad companies, and evaluate the long-run elasticity (LRE) of the TFP with respect to the adoption rates of heavy rails and concrete sleepers. The empirical results indicate that a 1% increase in concrete sleepers every year may increase (or ease the reduction in) the TFP of railroad company by about 1.554% after 11 years. A likely reason for the positive effect of installing concrete sleepers is that such equipment reduces not only the frequency of track maintenance, but also the number of trackmen required. Thus, subsidizing or promoting the replacement of wooden sleepers with concrete sleepers would also improve the long-term performance and viability of Japanese small and medium-sized passenger railroad companies.

Lastly, in Chapter 5, we first summarize the empirical analyses. Then, we describe the limitations common to all of the empirical studies that form part of this thesis. These include a possible lack of generalizability of the empirical results, and the problem we faced constructing a capital variable to use in the empirical studies. Future research should reconsider these issues.

Chapter 2

Factors that Affect Technical Efficiency

2.1 Introduction

Japanese regional small and medium-sized passenger railroad companies face operational difficulties stemming from a reduction in the number of passengers and high facility costs, often resulting in deficits. Continuing to operate inefficiently in this situation will make supplying transport services difficult in future. Therefore, we need to discuss ways to improve their financial situation and long-term viability. Hence, we need to investigate which types of railroad companies operate inefficiently.

Efficiency or inefficiency can be measured by estimating, for example, a distance function. We explain the distance function later. Many previous studies have investigated the efficiency of railroads by estimating distance functions. For example, Coelli and Perelman (1996) and Coelli and Perelman (2000) estimated a distance function for European railroads, which they used to predict the companies' efficiency. Baños-Pino et al. (2002) found inefficiency in Spanish public railroads. Atkinson et al. (2003) estimated a distance function and predicted the efficiency score of railroads in the United States. Lan and Lin (2006) conducted international comparisons among 39 railroad systems worldwide. Cullmann et al. (2012) used data on German and Swiss urban public transport systems to estimate a distance function accounting for time-invariant network characteristics. Bougna and Crozet (2016) used data on European railroads to investigate the relationship between the railroad liberalization process and efficiency. However, the efficiency of Japanese regional small and medium-sized passenger railroad companies has received little attention.

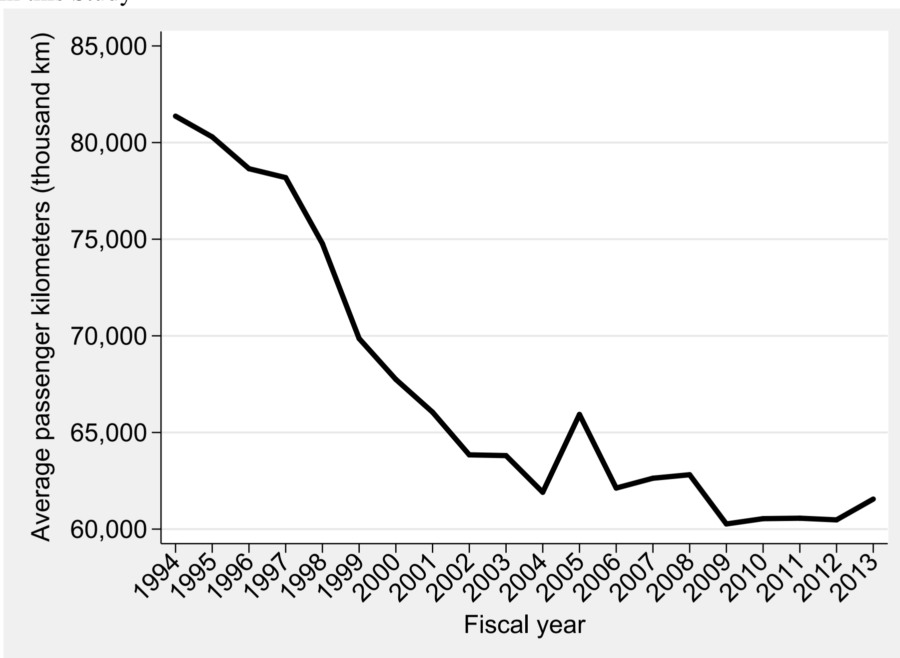
Therefore, we investigate those factors that affect the efficiency of Japanese regional small and medium-sized passenger railroad companies by estimating a distance function for these companies. The empirical results suggest that railroad companies that transport mainly long-distance passengers have higher technical efficiency (TE) than those that transport passengers over shorter distances do. Furthermore, we find that railroad companies that transport mainly commuters are more technically efficient than are those that transport mainly non-commuters, such as tourists.

The remainder of this chapter is structured as follows. Section 2.2 explains the present situation facing Japanese small and medium-sized passenger railroad companies, and Section 2.3 sets the hypotheses to be tested. Section 2.4 describes the input distance function and TE. Section 2.5 explains the data used in the empirical analysis. Then, Section 2.6 presents our estimation results using the input distance function and the prediction results of TE, and Section 2.7 discusses the empirical results. Lastly, Section 2.8 concludes the chapter.

2.2 Background

As mentioned in Section 1.1, Japanese regional small and medium-sized passenger railroad companies face operational difficulties stemming from a reduction in the population along their lines and from high facility costs. The population reduction is the result of the country's decreasing birthrate. Another major factor causing a reduction in railroad passengers is the increasing level of private car ownership. Figure 2.1 plots the changes in the average passenger kilometers of 32 Japanese regional small and medium-sized passenger railroad companies that existed during the study period (FY 1994–2013). Here, passenger kilometers is calculated as the number of passengers multiplied by the train vehicles' running kilometrage. The figure shows that the average passenger kilometers continued to decrease every year until FY 2004. Then, although it increased for a short period, it has never recovered the level of FY 1994.

Figure 2.1: Changes in the Average Passenger kilometers of the 32 Railroad Companies in this Study



Source: Author's diagram using Annual Rail Statistics data.

2.3 Hypotheses

We tested the following two hypotheses econometrically. The first hypothesis is that railroad companies that transport mainly long-distance passengers are more technically efficient than those that transport mainly short-distance passengers. Here, the longer the distance per passenger boarding, the higher is the value of passenger kilometers (the output in this study). This may make transportation more efficient.

The second hypothesis is that railroad companies that transport mainly commuters are more technically efficient than those that transport mainly other types of passengers (e.g., tourists, shoppers, outpatients, etc.). If there is stable demand for the transportation services of companies that transport mainly commuters, they may be more efficient (Nakanishi, 2008).

2.4 Model

This chapter estimates the railroad companies' input distance function in order to predict their TE. An input distance function can be used when companies have more control over their inputs than they do over their outputs (Coelli et al., 2005). We assume that the railroad companies produce one output (passenger kilometers) from three inputs (fixed assets, electricity consumption, and number of employees). Because this output is affected by demand factors such as the population along their lines, companies find it difficult to control their output. Thus, using an input distance function may be supported in this study.

We explain the input distance function for the case in which a company uses multiple inputs to produce a single output. Before defining the input distance function, we define the company's production function:

$$y = f(\boldsymbol{x}), \tag{2.1}$$

where y is the output and $\boldsymbol{x}$ is a vector of inputs. If the number of (variable and fixed) inputs is $\tilde{M}$, then the vector of inputs is

$$\boldsymbol{x} = (x_1, x_2, \cdots, x_{\tilde{M}})'. \tag{2.2}$$

Then, the input distance function is defined as follows:

$$d(y, \boldsymbol{x}) = \max_{\rho} \{\rho : f(\boldsymbol{x}/\rho) \geq y\}. \tag{2.3}$$

The input distance function $d(.,.)$ has the following properties:

1. $d(y, \boldsymbol{x})$ is non-decreasing in each input level;
2. $d(y, \boldsymbol{x})$ is non-increasing in each output level;
3. $d(y, \boldsymbol{x})$ is homogeneous of degree one in the input vector;
4. $d(y, \boldsymbol{x})$ is concave in the input vector;
5. if the combination of the input level, $\boldsymbol{x}$, can produce y, then $d(y, \boldsymbol{x})$ is greater than or equal to unity;
6. if $\boldsymbol{x}$ is the minimum combination of the input level that can produce y, then $d(y, \boldsymbol{x})$ is equal to unity.

Consider the case in which the company uses two inputs to produce one output. Figure 2.2 shows an isoquant line on a two-dimensional plane. The horizontal axis is the level of the first input, x_1, and the vertical axis is that of the second input, x_2. The isoquant line is plotted as the downward-sloping curve, and indicates the minimum combinations of the quantities of x_1 and x_2 capable of producing a constant quantity, y, of the output.

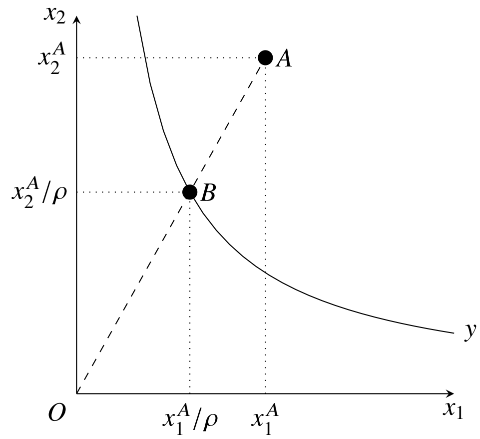
The company with a quantity of output y produces (transports) at point A: the quantities of the first and second inputs are x_1^A and x_2^A, respectively. The same output quantity can be produced (transported) at point B on the isoquant line. In other words, the company can reduce the quantities of both inputs by $1/\rho$ without reducing the level of output. Thus, ρ or OA/OB is the maximum scalar by which we are able to divide the quantities of all inputs, without changing the output quantity. In this case, the value of the input distance function is ρ. See Coelli et al. (2005) and Kumbhakar et al. (2015) for details.

According to Coelli et al. (2005), the (input-oriented) TE of a company is expressed in terms of the input distance function as

$$TE = \frac{1}{d(y, \boldsymbol{x})}. \tag{2.4}$$

In the case explained in Figure 2.2, the TE is OB/OA. Based on the properties of the input distance function, the TE is smaller than or equal to unity if the combination of

Figure 2.2: Isoquant Line and Distance Function, the Maximum ρ



Source: Author's diagram, with reference to Coelli et al. (2005) and Kumbhakar et al. (2015).

inputs can produce a constant output. If the TE of a company is smaller than unity, then the company is technically inefficient. Furthermore, the company is technically efficient if its TE is equal to unity.

Now, we express the input distance function as an empirical model. With reference to Atkinson et al. (2003), Bogart and Chaudhary (2013), and Deshpande and Weisskopf (2014), we assume that the railroad companies use three inputs to produce one output as a passenger transportation service, and that there is one output attribute. The Cobb–Douglas input distance function for company i at year t is expressed as follows:

$$\begin{aligned}\ln d_{it} &= \beta_{D0} + \beta_{DY} \ln y_{it}^{PKM} + \beta_{DOA} \ln OA_{it} + \beta_{DK} \ln k_{it} + \beta_{DM} \ln m_{it} \\ &\quad + \beta_{DL} \ln l_{it} + \beta_{DT} t + v_{Dit}, \end{aligned} \tag{2.5}$$

$$v_{Dit} \sim N\left(0, \sigma_v^2\right), \tag{2.6}$$

where d_{it} is the input distance, y_{it}^{PKM} is the output (passenger kilometers), OA_{it} is the output attribute, k_{it} is capital, m_{it} is an intermediate input, l_{it} is labor, and v_{it} is a two-sided disturbance term.

As mentioned previously, the input distance function is non-decreasing, homogeneous of degree one, and concave in the inputs. Because (2.5) is a Cobb–Douglas type function, it is non-decreasing and concave in inputs when β_{DK}, β_{DM}, and β_{DL} are all non-negative. After the estimation, we check whether the estimated input distance function satisfies these two properties. For the homogeneity property, we impose the following linear restriction on the function before the estimation:

$$\beta_{DK} + \beta_{DM} + \beta_{DL} = 1. \tag{2.7}$$

The input distance, the dependent variable of (2.5), is unobservable. Therefore, the distance function needs to be rearranged by moving $\ln d_{it}$ to the right-hand side, and making the left-hand side dependent variable observable.

Substituting (2.7) into (2.5), rearranging, and assuming a probability distribution on unobservable $\ln d_{it}$, we obtained the following model to be estimated:

$$
\begin{aligned}
-\ln k_{it} &= \beta_{D0} + \beta_{DY} \ln y_{it}^{PKM} + \beta_{DOA} \ln OA_{it} + \beta_{DM} \ln \tilde{m}_{it} + \beta_{DL} \ln \tilde{l}_{it} \\
&\quad + \beta_{DT} t + v_{Dit} - u_{Dit}, && (2.8) \\
v_{Dit} &\sim N\left(0, \sigma_v^2\right), && (2.9) \\
u_{Dit} &\sim N^+\left(\alpha_{it}, \sigma_u^2\right), && (2.10) \\
u_{Dit} &= \alpha_{it} + w_{Dit} \\
&= \alpha_0 + \alpha_{PRU} \ln PRU_{it} + \alpha_{NRP} \ln NRP_{it} + \alpha_T t + w_{Dit} && (2.11) \\
&\geq 0, \\
w_{Dit} &\geq -\alpha_{it}, && (2.12)
\end{aligned}
$$

where $\tilde{m}_{it} = m_{it}/k_{it}, \tilde{l}_{it} = l_{it}/k_{it}, u_{Dit} = \ln d_{it}$. The logarithm of the input distance, u_{Dit}, is a one-sided random variable that takes non-negative values. This random variable is distributed according to a truncated normal distribution, with the truncation point at zero: the (before-truncation) mean is α_{it} and the (before-truncation) variance is σ_u^2. Furthermore, u_{Dit} is affected by several factors: a passengers' route-use ratio (PRU_{it}), the non-rail-pass passenger ratio (NRP_{it}), and the time trend t. The α_{it} equation also has a disturbance term, w_{Dit}, which is distributed according to a truncated normal distribution, with the truncation point at $-\alpha_{it}$: the (before-truncation) mean is zero and the (before-truncation) variance is σ_u^2, as is the variance of u_{Dit}.

The model composed of (2.8)–(2.12) shows the input distance of a railroad company as inefficient, and is expressed as a stochastic frontier model. This is in line with the model proposed by Battese and Coelli (1995): u_{Dit} is assumed to be a function of some variables. See Coelli et al. (2005) for details of the Cobb–Douglas input distance function. We jointly estimate (2.8), called the input distance function, and (2.11), called the inefficiency function, based on the assumptions of the random variables' distribution (2.9), (2.10), and (2.12) using the maximum likelihood (ML) method: a one-step estimation.

Of course we can conduct a two-step estimation: estimating the distance frontier (2.8) using the ML method in the first stage, and regressing the predicted value of u_{Dit} on the explanatory variable of (2.11) in the second stage (Pitt and Lee, 1981; Kalirajan and Flinn, 1983; Kalirajan, 1989). However, Battese and Coelli (1993, 1995) pointed out that the two-step estimation contradicts the assumption of u_{Dit}. The first-stage estimation of the distance function assumes that u_{Dit}s is independently and identically distributed. Thus, regressing the predicted value of u_{Dit} on other variables in the second stage contradicts the assumption of u_{Dit}s' independent distribution. Battese and Coelli (1995) proposed the one-step simultaneous estimation in order to overcome this contradiction. Thus, we adopt their proposed estimation.

For a purely competitive industry, assuming the distance function to be a Cobb–Douglas type is not appropriate because this type of the function is not concave in output (Klein, 1974). In contrast, this problem does not arise for a regulated industry (Klein, 1974). Furthermore, this curvature problem is not serious when our primary interest is to obtain technical measures, even though the industry is purely competitive (Coelli and Perelman, 1996, 2000). In Japan, the government regulates the railroad industry in terms of fares, among other aspects. Thus, a Cobb–Douglas distance function may not cause a serious problem in this study.

Based on (2.4) and the definition of u_{Dit}, the TE is expressed in terms of u_{Dit} as

$$TE_{it} = \frac{1}{d_{it}} = \exp(-u_{Dit}). \tag{2.13}$$

2.5 Data

This chapter adopts panel data on Japanese small and medium-sized passenger railroad companies that had routes in regional areas from FY 1994 to FY 2013; the companies include private and third-sector companies. In Japan, third-sector companies are those with both private and public stakeholders. The data are taken from the "Annual Rail Statistics," published by the Ministry of Land, Infrastructure, Transport and Tourism, and the "Domestic Corporate Goods Price Index, All Commodities," published by Bank of Japan.

We omit some companies from the data. First, we omit companies that operate only cable cars, ropeways, or trolleybuses because their production technology and cost structures may differ from those of ordinary railroad companies. Second, with regard to energy, our data include companies that use electric vehicles only. Some Japanese railroad companies use diesel vehicles that run on oil, or steam locomotives that consume coal. However, the construction of the energy consumption variable is difficult if there are multiple types of energy in the sample because the units of measurement differ in each case (e.g., kilowatt-hour for electricity, kiloliter for oil). Thus, we omit companies that use diesel vehicles and steam locomotives from the sample. Third, we omit third-sector railroad companies that operate routes that run along high-speed lines and that were operated by private companies before the high-speed lines opened. The routes that these companies operate are called *heiko zairaisen*. These companies may have a different input component ratio from that of other companies. Thus, including these companies would make the estimation worse. Fourth, we omit type-II and type-III railroad companies from our data. In Japan, railroad companies are classified into three types (types I, II, and III). Of these, type-I railroad companies own track facilities and operate transport services. Type-II railroad companies also operate transport services but do not have track equipment, and their transportation technology may differ from that of type-I companies. Type-III railroad companies own track facilities, but do not operate a transport service. Thus, there are no data related to transport for type-III companies, and we cannot estimate a distance function for type-III companies. Finally, we omit companies that have too many missing or incorrect values in the data.

In this study, we focus on passengers. Therefore, we do not analyze companies that operate freight services only.[1] This is because passenger services are the main form of railroad transportation in Japan.

The final sample includes 45 companies. However, our data comprise an unbalanced panel: of the 45 companies, only 32 existed from FY 1994 to FY 2013.

There were several missing values, even when companies existed during the study period. Thus, we substitute the mean values of the previous and the following years for the missing value. For example, if the value for FY 2008 is missing, we substitute the mean value of FY 2007 and FY 2009 for the missing value in FY 2008.

Several values were obviously incorrect and, hence, were adjusted. For example, the energy consumption of Ueda Kotsu (renamed Ueda Dentetsu in FY 2007) in FY 2005 is indicated as 1,828 kWh. This is obviously an error because the consumption for the other years run into seven digits (e.g., 1,829,362 kWh in FY 2006). In this case, the FY 2005 consumption was treated as 1,828,000 kWh for comparability across years.

Furthermore, we divided fixed assets by the domestic corporate goods price index, with a base year of 2010, deflating the values to 2010 prices.

The descriptive statistics and definitions of the variables used in this study are

[1]We also exclude Mizushima Rinkai Tetsudo, a mainly freight transportation company that also offers passenger services.

Table 2.1: Descriptive Statistics for the Distance Function

Variable	Mean	Median	Minimum	Maximum	Standard deviation
Passenger kilometers (thousand people kilometers)	61,574.96	32,040.00	1,287.00	746,895.00	94,791.08
Average trip length (km/person)	8.58	6.72	3.31	56.51	7.13
Fixed asset (million yen)	5,838.65	2,110.57	12.49	84,789.57	12,868.16
Electricity (thousand kWh)	7,933.62	5,138.34	261.86	67,556.32	10,527.13
Labor (people)	132.94	91.00	13.00	948.00	138.02
Time trend (FY 1994=1)	10.55	11.00	1.00	20.00	5.76
Passengers' route-use ratio	0.38	0.39	0.05	0.95	0.18
Non-rail-pass passenger ratio	0.51	0.50	0.23	0.93	0.15

Note: The number of observations is 785.

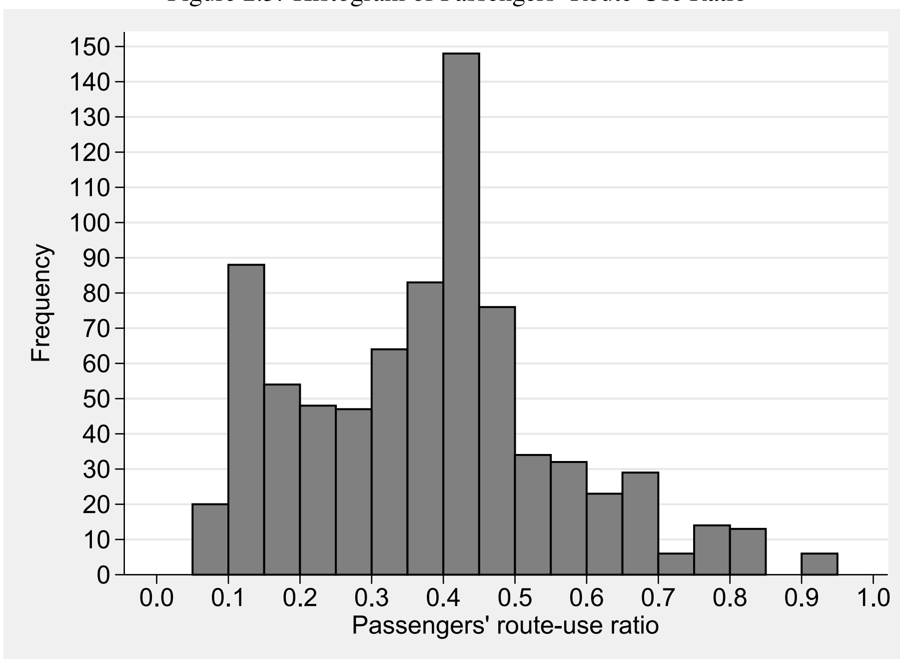
shown in Tables 2.1 and 2.2, respectively.[2] We constructed these variables following Atkinson et al. (2003), Mizutani and Uranishi (2007), Mizutani et al. (2009), Bogart and Chaudhary (2013), and Deshpande and Weisskopf (2014). The passenger kilometers, the average trip length, the fixed asset, and the electricity correspond to the output, its attribute, the capital, and the intermediate input in the previous section, respectively. As shown in Table 2.1, the passengers' route-use ratio ranges from 5% to 95%, and the non-rail-pass passenger ratio ranges from 23% to 93%. This suggests that there are large difference in Japanese small and medium-sized passenger railroad companies in terms of their transportation distance and their main types of passengers.

Histograms of passengers' route-use and the non-rail-pass passenger ratio are presented in Figures 2.3 and 2.4, respectively. These figures also show the large variation in transportation distance of one boarding and the main types of passengers.

As shown in Table 2.2, we use tangible fixed assets as the capital (fixed asset) variable. Several studies, such as Bogart and Chaudhary (2013), defined capital as

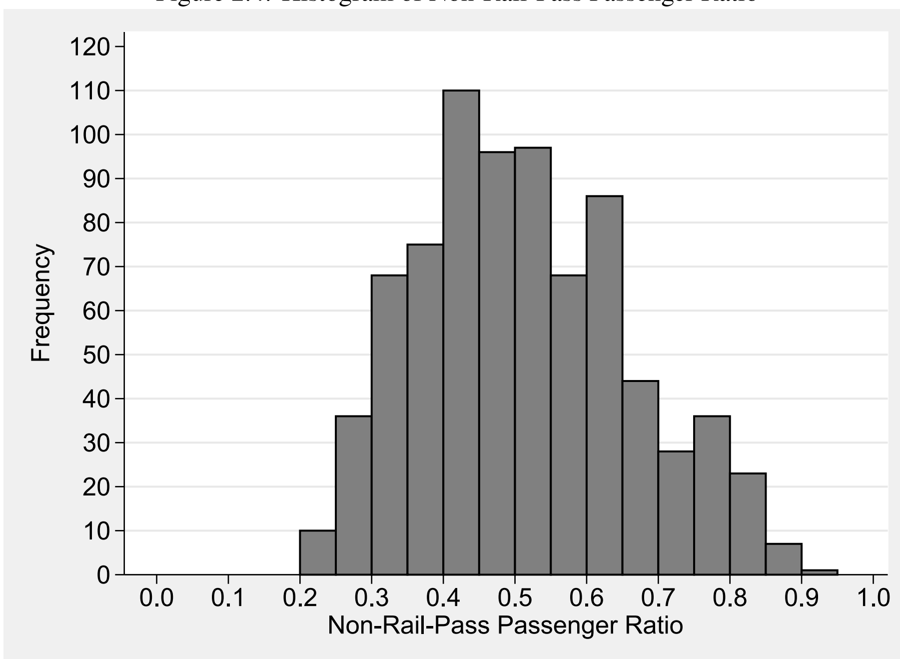
[2]For the definitions in Table 2.2, the passengers' route-use ratio is affected by the number of routes the company owns: the values of this variable are necessarily small for companies that have many short distance routes. One way to handle this is to multiply the passengers' route-use ratio by the company's number of routes. However, when we estimated the models using this definition, some parameters did not converge.

Figure 2.3: Histogram of Passengers' Route-Use Ratio



Source: Author's diagram using Annual Rail Statistics data.

Figure 2.4: Histogram of Non-Rail-Pass Passenger Ratio



Source: Author's diagram using Annual Rail Statistics data.

Table 2.2: Definitions of Variables for the Distance Function

Variable	Definition
Passenger kilometers	The number of passengers multiplied by running distance of train vehicles
Average trip length	Passenger kilometers divided by the number of passengers
Fixed asset	Sum of railroad exclusive and related tangible fixed asset
Electricity	Electricity consumption
Labor	The number of employees
Passengers' route-use ratio	Average trip length divided by operating kilometers
Non-rail-pass passenger ratio	The number of passengers who did not use a rail pass, divided by the total number of passengers

the capital stock estimated using the perpetual inventory method. However, estimating capital stock requires equipment investment data, which are unavailable for Japanese railroad companies.[3] Thus, we use fixed assets instead of capital stock.

2.6 Empirical Results

Table 2.3 presents the estimation results of the model composed of (2.8)–(2.12). We estimate the model with and without incorporating the inefficiency factors.

First, we describe the estimation results for the parameters of the inefficiency function of Battese and Coelli (1995) model using the inefficiency determinants shown in the third column of Table 2.3. The coefficient of the log of the passengers' route-use ratio shows a negative sign and statistical significance at the 1% significance level. The coefficients of the log of the non-rail-pass passengers' ratio shows a positive sign and statistical significance at the 5% significance level. In contrast, the coefficient of the time trend of the inefficiency function does not show statistical significance at any conventional significance level.

Second, we explain the Battese and Coelli (1995) models, with and without inefficiency determinants, in terms of information criteria. Here, the Akaike and

[3]Tanaka (2010) proposes an estimation method for equipment investment and capital stock in Japanese public subways. Although we attempted estimating regional small and medium-sized railroad companies' investment, certain nominal gross investments were estimated to be negative. This can be attributed to extremely small equipment investments or extremely large fixed asset removals, unlike public subway companies' investments and removals.

Bayesian information criteria become smaller when incorporating the inefficiency determinants.

Next, we check whether the estimated models satisfy the monotonic properties: non-decreasing in inputs and non-increasing in output. The coefficients of the log of passenger kilometers show negative signs and statistical significance at the 1% significance level for the Battese and Coelli (1995) models, with and without the inefficiency determinants. Thus, these estimated input distance functions are non-increasing in output. The coefficients of the logs of electricity and labor show positive signs and statistical significance at the 1% significance level. However, the coefficients of the log of capital, estimated by subtracting the coefficients of the logs of electricity and labor from one, show negative signs for the Battese and Coelli (1995) models (−0.009 without the inefficiency determinants, and −0.038 with the inefficiency determinants). Thus, the estimated Battese and Coelli (1995) models do not satisfy the property of being non-decreasing in inputs.

Then, we tried controlling for railroad companies' time-invariant individual effects. Letting μ_{Di} be the individual effect, adding it to (2.8), and suppressing the constant term, β_{D0}, we obtain

$$\begin{aligned} -\ln k_{it} = \beta_{DY} \ln y_{it}^{PKM} + \beta_{DOA} \ln OA_{it} + \beta_{DM} \ln \tilde{m}_{it} \\ + \beta_{DL} \ln \tilde{l}_{it} + \beta_{DT} t + \mu_{Di} + v_{Dit} - u_{Dit}. \end{aligned} \tag{2.14}$$

This is the true fixed effect (TFE) model proposed by Greene (2005a,b). This model separates companies' time-invariant individual effects from their time-variant inefficiency. Also, it allows the individual effects to be correlated with the independent variables of the function (Greene, 2005a). The method separating the individual effects from the inefficiency have been applied in some transportation literature such as Walter (2011) and Nieswand and Walter (2013).[4] For the TFE model, we simultaneously estimate the input distance frontier, including individual effects (2.14), and the inefficiency function (2.11) using the assumptions of the random variables' distributions (2.9), (2.10), and (2.12). See Greene (2005a,b) and Kumbhakar et al. (2015) for details of the TFE model.

[4] Walter (2011) applied the true *random* effect (TRE) model to the German local public buses and railroads, and Nieswand and Walter (2013) applied it to the German local public buses. The TRE model assumes that the time-invariant individual effects are random and uncorrelated with any independent variables of the function, and was also proposed by Greene (2005a,b).

Note that the TFE model does not always yield unreasonably small or statistically insignificant coefficients for the inefficiency determinants (logs of the passengers' route-use ratio and non-rail-pass passenger ratio, as well as the time trend), even though the within-individual variation of the inefficiency determinants is small. This is because the inefficiency function (2.11) does not include individual effects on the right-hand side.

The estimations of the TFE models yield results that are consistent with economic theory and that are robust for the signs of the coefficients on the inefficiency determinants. The results of the TFE models with and without the inefficiency determinants are presented in the fourth and last columns of Table 2.3. The coefficients of the log of capital in the TFE models have a positive sign (0.011 for the without-inefficiency determinants model, and 0.009 for the with-inefficiency determinants), although they are still low. Thus, the estimated TFE models satisfy the properties of being non-decreasing in inputs and non-increasing in output. With regard to the coefficients of the inefficiency function, the coefficient of the log of passengers' route-use ratio shows a negative sign and statistical significance at the 1% significance level. This is essentially the same result as that of the model without individual effects (Battese–Coelli's model). The coefficient of the log of non-rail-pass passengers' ratio shows positive sign and statistical significance at the 1% significance levels: the same sign as that in Battese–Coelli's model, and stronger statistical significance. Furthermore, the absolute values of both coefficients from the TFE model are larger than those from the Battese-Coelli's model. Moreover, the Akaike and Bayesian information criteria of the TFE model with inefficiency determinants are smaller than those of the Battese and Coelli (1995) model with inefficiency determinants. Hence, incorporating railroad companies' time-invariant individual effects and separating them from time-variant inefficiency has improved the results in terms of their consistency with the properties of the input distance function and the likelihood of the parameters.

Based on these results, we accept the TFE model incorporating inefficiency determinants shown in the fifth column of Table 2.3. This is because the model satisfies the monotonicity conditions and its information criteria are the smallest of the four models. Thus, we focus on this model below.

We predict the TE using estimates of the input distance function. According to Battese and Coelli (1993) and StataCorp LLC (2015), the technical efficiency for each

Table 2.3: Estimation Results of the Distance Function

	Battese and Coelli (1995) model		True fixed effect model	
	Without inefficiency determinants	With inefficiency determinants	Without inefficiency determinants	With inefficiency determinants
Parameter of input distance frontier:				
Log of passenger kilometers	−0.763***	−0.639***	−0.498***	−0.475***
	(0.010)	(0.011)	(0.021)	(0.017)
Log of average trip length	0.156***	−0.017	0.095	0.105
	(0.019)	(0.025)	(0.085)	(0.077)
Log of electricity	0.490***	0.582***	0.397***	0.452***
	(0.026)	(0.030)	(0.022)	(0.020)
Log of labor	0.519***	0.456***	0.592***	0.539***
	(0.026)	(0.028)	(0.022)	(0.020)
Time trend	−0.006***	−0.006	−0.000	−0.001**
	(0.002)	(0.005)	(0.001)	(0.001)
Constant term	−1.902***	−3.163***	—	—
	(0.253)	(0.316)	—	—
Company-level individual effects	No	No	Yes	Yes
Parameter of inefficiency function:				
Log of passengers' route-use ratio	—	−0.366***	—	−1.263***
	—	(0.026)	—	(0.447)
Log of non-rail-pass passenger ratio	—	0.059**	—	3.296***
	—	(0.026)	—	(1.124)
Time trend	—	0.000	—	0.015
	—	(0.005)	—	(0.016)
Constant term	−0.041	0.212**	−5.240	−1.461
	(0.121)	(0.094)	(6.360)	(0.890)
Parameter of Inefficiency and disturbance term:				
Standard deviation of inefficiency term	0.247***	0.199***	0.761*	0.345***
	(0.015)	(0.010)	(0.421)	(0.075)
Standard deviation of disturbance term	0.202***	0.039	0.036***	0.049***
	(0.018)	(0.052)	(0.004)	(0.003)
Ratio of standard deviation of inefficiency term	1.223***	5.095***	21.145***	7.001***
to that of disturbance term	(0.032)	(0.063)	(0.419)	(0.076)
Likelihood and information criteria:				
Log-likelihood	−11.810	165.878	764.365	913.802
Akaike's information criterion	41.620	−307.756	−1422.729	−1715.605
Bayesian information criterion	83.611	−251.768	−1175.448	−1454.326

Notes: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors based on the outer product of the gradient vectors are shown in parentheses. The true fixed effect model includes each company's dummy variables as independent variables of the frontier (the constant term is suppressed). The number of observations is 785.

company and year is predicted as

$$\begin{aligned}\widehat{TE}_{it} &= E\left[\exp(-u_{Dit}) \mid rv_{Dit}\right] \\ &= \left\{\frac{\Phi(\alpha_{*it}/\sigma_{*}) - \sigma_{*}}{\Phi(\alpha_{*it}/\sigma_{*})}\right\} \exp\left(-\alpha_{*it} + \frac{1}{2}\sigma_{*}^{2}\right),\end{aligned} \tag{2.15}$$

where $rv_{Dit} = v_{Dit} - u_{Dit}$, $\alpha_{*it} = (\sigma_v^2 \alpha_{it} - \sigma_u^2 rv_{Dit})/(\sigma_v^2 + \sigma_u^2)$, $\sigma_*^2 = \sigma_v^2 \sigma_u^2/(\sigma_v^2 + \sigma_u^2)$, and $\Phi(.)$ is the cumulative density function of the standard normal distribution. The mean value of the predicted TE from the TFE model with inefficiency determinants is 0.931, and its standard deviation is 0.103. The TE values of some companies are less than 0.8.

2.7 Discussion

Here, we discuss the factors affecting the TE of the railroad companies. With regard to the estimation results of the accepted TFE model incorporating the inefficiency factors, the passengers' route-use ratio is negatively and significantly correlated with inefficiency. This suggests that railroad companies that transport mainly long-distance passengers are more technically efficient than are those that transport mainly short-distance passengers. This may be because a longer distance per boarding means the value of passenger kilometers (the output) becomes higher. Thus, the first hypothesis described in Section 2.3 is supported.

Furthermore, the non-rail-pass passenger ratio is positively and significantly correlated with inefficiency. This indicates that railroad companies that transport commuters are more efficient than those that transport other types of passengers. This may be because railroad companies with a high ratio of rail-pass passengers transport a stable number of passengers every year. This result is in line with those of Yamashita (2003) and Nakanishi (2008).[5] Hence, the second hypothesis is also supported.

As a related point, railroad companies that transport mainly non-commuters, such as tourists, may be less efficient because they may transport a variable number of passengers every year. However, there may be another reason why these railroad companies operate inefficiently. That is, they may use too much of their fixed or variable inputs to supply their transport services. As described in Sections 2.1 and 2.2,

[5] Yamashita (2003) and Nakanishi (2008) investigated the efficiency of public buses in Japan.

some Japanese small and medium-sized passenger railroad companies face high facility costs. Overuse of fixed inputs will cause high facility costs. In the next chapter, we investigate the relationship between the non-rail-pass passenger ratio and the level of fixed costs in terms of returns to density.

2.8 Conclusion

This chapter econometrically tested two hypotheses using panel data of Japanese regional small and medium-sized passenger railroad companies. The first hypothesis is that railroad companies that transport mainly long-distance passengers are more technically efficient than are those that transport mainly short-distance passengers. The second hypothesis is that railroad companies that transport mainly commuters are more technically efficient than are those that transport mainly non-commuters, such as tourists.

In order to conduct these empirical analysis, we estimated the input distance function and the inefficiency function using the panel data.

The empirical results support both hypotheses. We obtained these results because the value of passenger kilometers (output) increases with the distance traveled using the transport service per boarding. In addition, railroad companies with a high ratio of rail-pass passengers transport a stable number of passengers every year.

Railroad companies that transport mainly non-commuters may transport a variable number of passengers, or may overuse their fixed inputs, which are sources of fixed costs. We examine the possibility of high fixed costs in the next chapter.

The empirical analysis in this chapter has several limitations. First, we estimated a Cobb–Douglas type function that imposes a strong assumption (i.e., constant substitution elasticity). When we tried to estimate a translog input distance function in order to relax this assumption, the estimated function did not satisfy concavity. As mentioned in Section 2.4, specifying a Cobb–Douglas function is not serious in our case. However, future work should identify why the translog function yields poor estimates. Obtaining estimates that are consistent with economic theory by estimating a more flexible form of function (with weaker assumptions) would contribute to a more precise analysis. Second, we omitted certain companies, such as those that use diesel vehicles, among others, from the sample. Therefore, the results may not be generalizable for Japanese regional small and medium-sized passenger railroad companies. In order to ensure consistency in this thesis, the railroad companies included in this chapter's sample are the same as those included in the next chapter's sample. In the analysis of the next chapter, we could not obtain better estimates for the cost system when we included companies such as diesel companies in the sample. Finally, the coefficients of capital in the input distance functions were calculated as being quite small (negative for the estimation without individual effects, and around 0.01 for the estimation with individual effects). One of the reasons of this issue might be that we use fixed assets instead of capital stock as the capital variable. However, as mentioned in Section 2.5, constructing a capital stock variable is difficult owing to a lack of data. Because of these limitations, we need to carefully interpret our findings. Nevertheless, this chapter contributes to measuring the TE of Japanese regional small and medium-sized railroad companies and identifying the factors that affect TE.

Chapter 3

Factors that Affect Returns to Density

3.1 Introduction

This chapter evaluates the returns to density (RTD) of regional small and medium-sized passenger railroad companies in Japan. As such, we investigate whether these companies benefit from economies of density (EOD), and determine the factors that affect their RTD. The presence of EOD indicates a decrease in average costs when the transport service volume (e.g., the running kilometrage of train vehicles, or vehicle kilometers) increases, under some conditions. The intensity of EOD is measured by the RTD. The RTD shows an increasing rate in transport volume caused by proportional increases in all inputs. Fixed costs are one source of EOD and RTD (Graham et al., 2003). Thus, we can determine whether a company's fixed costs are high by calculating the RTD and measuring the EOD.

In general, the RTD decreases with the volume of transport services in industries such as the railroad industry. This is because the total costs of companies with high vehicle kilometers increases significantly when they add to this infrastructure, owing to the additional staff and facilities required. Thus, there may be a negative relationship between RTD and transport volume.

Savage (1997) and Wheat and Smith (2015) found a negative relationship between RTD and output. The former work analyzed the RTD of railroads in the United States and the latter did the same for the United Kingdom. Both found that railroads' average costs decrease as output (train vehicles' running time) increases. That is, the RTD gets smaller (and the EOD gets weaker) when output increases.

Japanese regional small and medium-sized passenger railroad companies face operational difficulties stemming from high facility costs, in many cases, resulting in deficits. Part of their facility costs are fixed costs.

If a railroad company has a good RTD, then it can reduce its average costs by increasing its transport services (additional vehicle kilometers) or by reducing its facilities (source of fixed costs). However, increasing the transport volume is not an appropriate solution in Japan because the number of passengers these companies transport is decreasing. Thus, in order to reduce their average costs and improving their long-term viability, they need to reduce their facilities (Tretheway et al., 1997).

The fixed costs of railroad companies in Japan are difficult to observe directly owing to a lack of data. Thus, we do so by calculating their RTD and then measuring their EOD. Furthermore, determining the factors that affect the RTD of railroad companies will help to improve the financial situation of Japanese regional small and medium-sized passenger railroad companies.

This chapter aims to determine the factors affecting the RTD of Japanese regional small and medium-sized railroad companies. To achieve this objective, we estimate a cost system composed of a translog variable cost function and input share functions using panel data on relevant companies. When estimating the system, we apply a hedonic cost function that accounts for the differences in the output characteristics (e.g., the average number of vehicles per train unit) of the companies, as well as the differences in the effects of these characteristics on the companies' marginal costs or RTD. By incorporating these factors, we are able to estimate the model (and calculate the RTD) precisely. Then, we calculate indices of RTD for all observations using the estimates from the cost system.

The empirical results indicate that all companies in the sample benefit from EOD during the study period. We also find that Japanese regional small and medium-sized passenger railroad companies that transport mainly commuting passengers have a lower RTD than those that mainly transport other types of passengers, such as tourists, shoppers, and outpatients. Thus, removing capital inputs (e.g., rolling stocks or tracks) that are no longer used would improve these companies' performance and long-run viability, especially those that transport non-commuters.

The remainder of this chapter is structured as follows. Section 3.2 defines RTD and EOD and explains how they are related to fixed costs. Then, as a background to this study, Section 3.3 explains the present situation faced by Japanese small and medium-sized passenger railroad companies. Section 3.4 describes the econometric cost system that we estimate, and Section 3.5 explains the data used in the empirical analysis. Section 3.6 presents the estimation results of the cost system and the calculation of the RTD. Section 3.7 discusses our empirical results. Lastly, Section 3.8 concludes the chapter, including a discussion on the limitations of the study and possible areas of future research.

3.2 Economies of Density and Returns to Density

The concept of economies of density (EOD) is important in the railroad industry, and many researchers, such as Savage (1997), Wheat and Smith (2015), and Harada (2016), have conducted studies to determine its value within the industry. The EOD describes the nature of the decrease in average costs when output (e.g., vehicle kilometers) increases, with the network size (e.g., distance of rail lines) held constant (Harris, 1977). Caves et al. (1984) defined EOD as the decrease in average costs when keeping a load factor (e.g., number of passengers per service) and the network size fixed. However, Xu et al. (1994) pointed out that holding the load factor fixed may not be appropriate, because some output characteristics (e.g., the load factor) also change when output increases. Thus, we follow Harris's definition of EOD.

The existence or intensity of EOD is measured by returns to density (RTD). The RTD describes the proportional increase in transport volume from a proportional increase in all inputs, holding the network size fixed (Caves et al., 1985; Smith et al., 2015). Specifically, the RTD indicates how much output increases when all inputs or total costs increase by 1%.

Therefore, the EOD and RTD show how the average costs change when increasing the output. If the RTD is greater than unity, this indicates increasing RTD or the presence of EOD. Thus, we can use the terms EOD and "increasing RTD" interchangeably (Caves et al., 1984). EOD (increasing RTD) means that a company can achieve a large increase in transport volume with a relatively small increase in inputs or total costs. In this case, the average costs decrease as the transport volume increases. On the other hand, if the RTD is less than unity, we have decreasing RTD and diseconomies of density. A decreasing RTD indicates that a company needs a relatively large increase in inputs or total costs in order to increase its transport volume. In this case, average costs increase as the transport volume increases.

Fixed costs are one of the sources of EOD and RTD (Graham et al., 2003), because EOD and RTD reflect changes in average costs, and average costs are affected by fixed costs. If a company has strong EOD (its RTD is significantly greater than unity), its fixed costs may be large relative to the transport volume. If observing a company's fixed costs is difficult, we can measure the RTD (and, thus, determine the intensity of EOD).

3.3 Background

Japanese regional small and medium-sized passenger railroad companies face operational difficulties stemming from a reduction in the population along their routes and high facility costs, often resulting in deficits. In FY 2011, facility costs accounted for about 45% of total costs (Kajimaya and Tokutake, 2013). Thus, it seems imperative that these companies reduce their facility costs, because they pose a major obstacle to the companies' operations.

Part of the facility costs are the companies' fixed costs. As mentioned previously, fixed costs are a source of economies of density (EOD) (Graham et al., 2003). However, as noted in Section 3.1, the fixed costs of railroad companies in Japan are difficult to observe, owing to a lack of data. Therefore, measuring the EOD enables us to determine the level of the fixed costs of these companies against their output.

If the railroad companies have increasing returns to density (RTD), then they can reduce their average costs by increasing their transport services (increasing their vehicle kilometers). However, this is difficult in Japan because the number of passengers is decreasing. Thus, in order to improve their performance and long-term viability, they need to reduce their facilities (Tretheway et al., 1997). For example, by removing tracks or rolling stocks that are no longer used, they can improve their financial situation. However, because such a capital adjustment takes time and incurs significant removal costs, reducing facilities and costs is a long-term project.

3.4 Empirical Model

We first define the short-run variable cost function of railroad companies. The short run in this study refers to the period in which companies cannot optimize the quantity of fixed inputs. The variable cost function for company i in year t is expressed as

$$c_{it} = c(\psi_{it}, \boldsymbol{w}_{it}, k_{it}, t), \tag{3.1}$$

where c_{it} is a variable cost, ψ_{it} is the output, $\boldsymbol{w}_{it}$ is a vector of variable input prices, and k_{it} denotes capital (fixed input). If the number of variable inputs is M, then the input-price vector is

$$\boldsymbol{w}_{it} = (w_{1it}, w_{2it}, \cdots, w_{Mit})'. \tag{3.2}$$

In the railroad industry, differences in the output characteristics of companies or between years may affect their marginal costs or RTD. Here, examples of output characteristics are the average number of passengers per train, average number of vehicles per train, and the number of vehicle types. To account for the differences in output characteristics in a parsimonious manner, we apply the hedonic cost function developed by Spady and Friedlaender (1978). Several studies have applied this function, including those of De Borger (1991), Wang and Liao (2006), Bitzan and Wilson (2007), Mizutani and Uranishi (2007), and Wheat and Smith (2015). Thus, by doing so, we are able to estimate the model (and calculate the RTD) more precisely.

We define the hedonic output function and substitute it into the variable cost function. The hedonic output function is defined as follows:

$$\psi_{it} = \psi\left(y_{it}^{VKM}, \boldsymbol{q}_{it}\right), \tag{3.3}$$

where y_{it}^{VKM} is the physical output (vehicle kilometers) and $\boldsymbol{q}_{it}$ is a vector of output characteristics. If the number of output characteristics is R, then the vector of output characteristics is defined as $q_{it} = (q_{1it}, q_{2it}, \cdots, q_{Rit})'$.

Substituting the hedonic output function into the variable cost function, we have

$$c_{it} = c\left(\psi\left(y_{it}^{VKM}, \boldsymbol{q}_{it}\right), \boldsymbol{w}_{it}, k_{it}, t\right). \tag{3.4}$$

Following Bitzan and Wilson (2007), Mizutani and Uranishi (2007), and Wheat and

Smith (2015), we assume the hedonic output function to be of Cobb–Douglas form:[1]

$$\psi_{it} = y_{it}^{VKM} \prod_{r=1}^{R} q_{rit}^{\Phi_r}. \tag{3.5}$$

Taking the logarithms of the variables except the time trend, applying a second-order Taylor expansion, and adding individual effect terms and a disturbance term, we obtain the following translog hedonic cost function:

$$\begin{aligned}
\ln c_{it}^{*} = {} & A_0 + A\left(\ln y_{it}^{VKM} + \sum_{r=1}^{R} \Phi_r \ln q_{rit}\right) + \sum_{m=1}^{M-1} B_m \ln w_{mit}^{*} + C \ln k_{it} + Dt \\
& + \frac{1}{2}AA\left(\ln y_{it}^{VKM} + \sum_{r=1}^{R} \Phi_r \ln q_{rit}\right)^2 + \frac{1}{2}\sum_{m=1}^{M-1}\sum_{d=1}^{M-1} BB_{md}\left(\ln w_{mit}^{*}\right)\left(\ln w_{dit}^{*}\right) \\
& + \frac{1}{2}CC\,(\ln k_{it})^2 + \frac{1}{2}DDt^2 + \sum_{m=1}^{M-1} AB_m\left(\ln y_{it}^{VKM} + \sum_{r=1}^{R} \Phi_r \ln q_{rit}\right)\left(\ln w_{mit}^{*}\right) \\
& + AC\left(\ln y_{it}^{VKM} + \sum_{r=1}^{R} \Phi_r \ln q_{rit}\right)(\ln k_{it}) + AD\left(\ln y_{it}^{VKM} + \sum_{r=1}^{R} \Phi_r \ln q_{rit}\right)t \\
& + \sum_{m=1}^{M-1} BC_m\left(\ln w_{mit}^{*}\right)(\ln k_{it}) + \sum_{m=1}^{M-1} BD_m\left(\ln w_{mit}^{*}\right)t + CD(\ln k_{it})t + \mu_{Ci} + v_{Cit},
\end{aligned} \tag{3.6}$$

where $c_{it}^{*} = c_{it}/w_{Mit}$, and $w_{mit}^{*} = w_{mit}/w_{Mit}$, for all $m = 1, 2, \ldots, M-1$. Here, μ_{Ci} is an individual effect, and v_{Cit} is the disturbance term. Following previous works, (e.g., Bitzan and Wilson, 2007), we subtracted the sample mean of the time trend from the original time trend. The other variables are divided by their sample means in order to serve as approximation points. As noted above, this function includes companies' individual effects.[2] This is because an estimation without individual effects will yield

[1]We also tried estimating the function under the assumption of translog hedonic output. However, in this case, the parameters did not converge when estimating the model.

[2]Many previous studies, such as Wheat and Smith (2015), include network length (operating kilometers, which represents the route length that a company operates) as one of the independent variables. However, the operating kilometers in our data are time-invariant, with the exception of one company. In other words, the individual effects include most of differences in the network lengths of the companies. Thus, we do not include operating kilometers as an independent variable of the variable cost function.

biased estimates of the RTD, owing to the correlation between the output and individual effects (Caves et al., 1985; Smith et al., 2015). When estimating this function, we capture this by including a dummy variable for each company other than the first company.

Restrictions of symmetry and homogeneity of degree one in input prices are imposed on (3.6). The symmetric restrictions are expressed as follows:

$$\forall m \neq d, BB_{md} = BB_{dm}. \tag{3.7}$$

In addition, the homogeneity restrictions are

$$\begin{aligned} &\sum_{m=1}^{M} B_m = 1, \sum_{m=1}^{M} AB_m = 0, \sum_{m=1}^{M} BC_m = 0, \sum_{m=1}^{M} BD_m = 0, \\ &\forall d, \sum_{m=1}^{M} BB_{md} = 0. \end{aligned} \tag{3.8}$$

The homogeneity restrictions are imposed in order to assume companies' cost minimizing behavior and to obtain better econometric estimates (Coelli et al., 2005).

By applying Shephard's lemma to the variable cost function, we obtain the following input share functions:

$$\begin{aligned} S_{mit} = B_m + \sum_{d=1}^{M-1} BB_{md} \ln w^*_{dit} + AB_m \left(\ln y_{it}^{VKM} + \sum_{r=1}^{R} \Phi_r \ln q_{rit} \right) \\ + BC_m \ln k_{it} + BD_m t + v_{mit} \quad \forall m = 1, 2, \ldots, M-1, \end{aligned} \tag{3.9}$$

where S_{mit} is the proportion (share) of the costs made up of the m-th variable input of the variable costs.

Of course, we can account for output characteristics without using the hedonic specification, by specifying an ordinary translog cost system that includes all squared and interaction terms of the log of the output and the log of the output characteristics. The benefit of estimating a hedonic cost system rather than the ordinary translog is that the model becomes more parsimonious (Smith et al., 2015).[3] That is, the number of

[3]We tried estimating the ordinary translog cost system by incorporating *all* (five) output characteristics. However, we obtained worse estimation results in this case. For example, the coefficient of the first-order term of the log of the output (vehicle kilometers) showed a negative sign and statistical insignificance, which is not consistent with economic theory.

parameters of the hedonic system to be estimated is smaller than that of the ordinary translog system.

We now have a hedonic cost system composed of (3.6) and (3.9). This is regarded as a nonlinear seemingly unrelated regression (SUR) model. We jointly estimate (3.6) and (3.9) using the nonlinear feasible generalized least squares (FGLS) method. See Smith et al. (2015) for details.

In order to check whether incorporating all output characteristics in this study affects the estimation results, we also estimate a generic cost system. This is an ordinary translog cost system *without* incorporating output characteristics other than the load factor. Then, we compare the results of the two systems. The generic (ordinary) translog variable cost function is expressed as follows:

$$\begin{aligned}\ln c_{it}^{*} = {} & A_0 + A_1 \ln y_{it}^{VKM} + A_2 \ln q_{2it} + \sum_{m=1}^{M-1} B_m \ln w_{mit}^{*} + C \ln k_{it} + Dt + \frac{1}{2}AA_{11}\left(\ln y_{it}^{VKM}\right)^2 \\ & + \frac{1}{2}AA_{22}(\ln q_{2it})^2 + \frac{1}{2}\sum_{m=1}^{M-1}\sum_{d=1}^{M-1} BB_{md}\left(\ln w_{mit}^{*}\right)\left(\ln w_{dit}^{*}\right) + \frac{1}{2}CC(\ln k_{it})^2 \\ & + \frac{1}{2}DDt^2 + AA_{12}\left(\ln y_{it}^{VKM}\right)(\ln q_{2it}) + \sum_{m=1}^{M-1} AB_{1m}\left(\ln y_{it}^{VKM}\right)\left(\ln w_{mit}^{*}\right) \\ & + AC_1\left(\ln y_{it}^{VKM}\right)(\ln k_{it}) + AD_1\left(\ln y_{it}^{VKM}\right)t + \sum_{m=1}^{M-1} AB_{2m}(\ln q_{2it})\left(\ln w_{mit}^{*}\right) \\ & + AC_2(\ln q_{2it})(\ln k_{it}) + AD_2(\ln q_{2it})t + \sum_{m=1}^{M-1} BC_m\left(\ln w_{mit}^{*}\right)(\ln k_{it}) \\ & + \sum_{m=1}^{M-1} BD_m\left(\ln w_{mit}^{*}\right)t + CD(\ln k_{it})t + \mu_{Ci} + v_{Cit},\end{aligned} \tag{3.10}$$

where q_{2it} is the load factor of one of the output characteristics. The other output characteristics are not incorporated in this function. The load factor that reflects the number of passengers carried may affect a railroad company's costs (Savage, 1997). Thus, in the generic model, we only incorporate a load factor for the output characteristics. Similarly to the hedonic model, the symmetry restrictions,

$$\forall m \neq d, BB_{md} = BB_{dm}, \tag{3.11}$$

and the homogeneity restrictions,

$$\sum_{m=1}^{M} B_m = 1, \sum_{m=1}^{M} AB_{1m} = 0, \sum_{m=1}^{M} AB_{2m} = 0, \sum_{m=1}^{M} BC_m = 0, \sum_{m=1}^{M} BD_m = 0,$$
$$\forall d, \sum_{m=1}^{M} BB_{md} = 0, \tag{3.12}$$

are imposed on (3.10).

Then, the input share functions are

$$\begin{aligned} S_{mit} &= B_m + \sum_{d=1}^{M-1} BB_{md} \ln w^*_{dit} + AB_{1m} \ln y^{VKM}_{it} + AB_{2m} \ln q_{2it} \\ &+ BC_m \ln k_{it} + BD_m t + v_{mit} \quad \forall m = 1, 2, \ldots, M-1. \end{aligned} \tag{3.13}$$

The generic cost system composed of (3.10) and (3.13) is regarded as a linear SUR model. Thus, we jointly estimate (3.10) and (3.13) using the (linear) FGLS method.

3.5 Data

Similarly to the previous chapter, we use panel data for Japanese small and medium-sized passenger railroad companies that have routes in regional areas. For the period FY 1994–2013 adopted in Chapter 2, we chose the period FY 2005—2013, during which a few railroad companies entered and exited the railroad transport market. The data sources are the same as those of the previous chapter: "Annual Rail Statistics," published by the Ministry of Land, Infrastructure, Transport and Tourism, and the "Domestic Corporate Goods Price Index, All Commodities," published by Bank of Japan.

We omit companies from the data based on same criteria as before: those that operate only cable cars, ropeways, or trolleybuses; those that use diesel vehicles that run on oil or steam locomotives that consume coal; third-sector railroad companies that operate routes called *heiko zairaisen*; companies with many missing and many incorrect data values; type-II railroad companies, which operate transport services, but do not have track equipment; and type-III railroad companies, which own track facilities, but do not operate a transport service. The construction of the energy price variable, which is one of the independent variables of the cost function, is difficult if there are multiple types of energy in the sample. The third-sector companies that operate *heiko zairaisen* have a different cost structure in that their material cost share is smaller than that of other companies. Thus, including these companies will make the estimation worse. See Section 2.5 for the definitions of third-sector companies in Japan and *heiko zairaisen*.

The final sample includes 40 companies. However, our data comprise an unbalanced panel. Of the 40 companies, 37 existed from FY 2005 to FY 2013, two companies were included during the period, and one was dropped from the sample.

There were several missing values, even when companies existed during the study period. Thus, similarly to the former chapter, we substitute the mean values of the former and the latter years for the missing values. Because there were also several obviously incorrect values, we adjusted these as well. For details on the imputing and adjusting procedure, see Section 2.5.

Furthermore, we divide all monetary variables such as variable costs, variable input prices, and fixed assets by the domestic corporate goods price index, with a base year of 2010, deflating them to 2010 prices.

The descriptive statistics and the definitions of the variables used in this study are shown in Tables 3.1 and 3.2, respectively. The variables are constructed following the works of Mizutani and Uranishi (2007), Mizutani et al. (2009), Wheat and Smith (2015), and Harada (2016). As shown in Table 3.1, the standard deviations of variable costs and fixed assets are quite high (approximately one billion yen for variable costs and 13 billion yen for fixed assets, respectively). This suggests that there are large differences in the scale of small and medium-sized railroad companies in Japan.

3.6 Results

3.6.1 Cost System

We estimate two specifications of the cost system: a generic model and a hedonic model. The variable cost function of the former is the ordinary translog specification with one output (vehicle kilometers) and one output characteristic (load factor). In contrast, the variable cost function of the latter has a hedonic output, with vehicle kilometers adjusted by five characteristic variables, on the right-hand side. For this specification, the load factor is included in the hedonic output function, although the load factor and

Table 3.1: Descriptive Statistics of Variables for the Cost System

Variable	Mean	Median	Minimum	Maximum	Standard deviation
Variable costs (thousand yen)	1,002,675.70	699,496.83	93,273.71	4,999,358.14	1,043,362.72
Vehicle kilometers (thousand km)	2,883.71	1,799.50	168.00	18,403.00	3,460.41
Average number of vehicles	2.29	2.01	1.00	6.12	0.97
Load factor (passengers per train)	43.94	37.43	8.96	141.61	27.28
Average number of tracks	1.20	1.04	1.00	2.00	0.32
Non-rail-pass passenger ratio	0.51	0.50	0.26	0.86	0.15
Number of vehicle types	2.60	3.00	1.00	6.00	1.25
Energy price (yen)	14.99	14.74	8.80	25.05	2.02
Wage (thousand yen)	4,031.76	4,058.64	1,113.74	7,054.37	994.02
Material price (thousand yen)	10,858.21	8,197.09	2,563.36	47,084.87	7,313.62
Fixed asset (million yen)	6,437.27	1,838.90	12.49	80,692.02	13,648.91
Time trend (FY 2005=1)	5.00	5.00	1.00	9.00	2.57
Energy share	0.12	0.12	0.04	0.22	0.04
Labor share	0.52	0.53	0.18	0.76	0.10
Material share	0.36	0.34	0.16	0.75	0.10

Note: The number of observations is 356.

Table 3.2: Definitions of Variables

Variable	Definition
Variable cost:	
Variable costs	Sum of labor, energy, and material costs
Physical output:	
Vehicle kilometers	Sum of running distance of own and other company's train vehicles after subtraction of vehicle kilometers of own and other's freight vehicles
Output characteristics:	
Average number of vehicles	Vehicle kilometers divided by train kilometers
Load factor	The number of passengers per train kilometers
Average number of tracks	Main track length that company owns divided by operating kilometers
Non-rail-pass passenger ratio	The number of passengers who did not use a rail pass, divided by the total number of passengers
Number of vehicle types	The number of company passenger vehicle types classified in Annual Rail Statistics
Variable input price:	
Energy price	Electricity expenditure per electricity consumption
Wage	Total annual wage per employee
Material price	Total material expenditure per composite material index
Capital (fixed input):	
Fixed asset	Sum of railroad exclusive and related tangible fixed asset
Proportion (share) of costs of variable input to variable costs:	
Energy share	Energy cost divided by variable costs
Labor share	Labor cost divided by variable costs
Material share	Material cost divided by variable costs

Notes: Train kilometers is the sum of the running kilometers of own and other companies' train units less the running kilometers of own and other companies' freight train units. Operating kilometers is the route length that the company operates. Total maintenance cost is the sum of the maintenance cost of the track, electric line, and train vehicles. Following Mizutani and Uranishi (2007) and Mizutani et al. (2009), we calculate the composite material index as follows:
Composite material index = (Maintenance cost of track and electric line)/(Total maintenance cost) × Operating km at the end of the fiscal year + (Maintenance cost of train vehicles)/(Total maintenance cost) × Total number of train vehicles.

its squared and cross-terms are not included as independent variables.

The estimation results of these cost system are shown in Table 3.3. The R-squared values of the variable cost functions in both models reported in the third row from the bottom in Table 3.3 are greater than 0.99. The coefficients and their standard errors from the hedonic model are reported in the fourth and fifth column of Table 3.3, respectively. For the hedonic model, the coefficients of four of the five output characteristics (hedonic parameters) show statistical significance at the 1% or 5% significance levels. Furthermore, the null hypothesis that all five coefficients of the output characteristics are zero is rejected at any conventional significance level: the chi-squared test statistic with five degrees of freedom is 52.63, with a p-value of 0.000.

We check that the estimated models satisfy the monotonicity and concavity conditions. Both models satisfy the conditions that the variable cost function is monotonically increasing with respect to the three input prices, non-decreasing with respect to output (vehicle kilometers for the generic model, and hedonic output for the hedonic model), and concave with respect to the input prices for all observations. The condition that the variable cost function is monotonically non-increasing with respect to capital (fixed assets) is satisfied for only about 60% or 70% of the observations. However, both models satisfy this condition at the sample mean of the variables because the coefficients of the first-order term of the log of fixed assets show a negative sign in both cases.[4] For details about the monotonicity and concavity conditions, see Kumbhakar et al. (2015) and Harada (2016).

Table 3.4 shows the correlation coefficients of the residuals of the variable cost and input share functions of the generic model. The correlation coefficient between the residuals of the labor and material share functions is approximately −0.9. The null hypothesis that each function is independent is rejected at any conventional significance level: the chi-squared test statistic with three degrees of freedom is 293.458, with a p-value of 0.000.

3.6.2 Returns to Density

Using the estimates of the cost system, we now calculate the RTD for all observations. Let RTD_{it}^{G} and RTD_{it}^{H} be the RTD for the generic and hedonic models, respectively,

[4]For the generic model, 57.9% of observations satisfy this monotonicity condition with respect to capital. For the hedonic model, 70.8% of observations satisfy the condition.

Table 3.3: Estimation Results of the Cost System

	Generic model		Hedonic model	
	Coefficient	Standard error	Coefficient	Standard error
Parameter:				
Log of vehicle kilometers	0.408***	0.099	0.319***	0.052
Log of load factor	0.076	0.076	—	—
Log of wage	0.552***	0.005	0.544***	0.005
Log of material price	0.333***	0.005	0.338***	0.004
Log of fixed asset	−0.079*	0.044	−0.073*	0.041
Time trend	0.002	0.002	0.001	0.002
1/2 × Square of log of vehicle kilometers	0.010	0.075	0.060	0.054
1/2 × Square of log of load factor	0.002	0.114	—	—
1/2 × Square of log of wage	0.063***	0.013	0.091***	0.010
1/2 × Square of log of material price	0.093***	0.007	0.103***	0.006
1/2 × Square of log of fixed asset	−0.023	0.018	−0.014	0.018
1/2 × Square of time trend	−0.001	0.002	−0.001	0.001
Log of vehicle kilometers × Log of load factor	−0.052	0.068	—	—
Log of vehicle kilometers × Log of wage	−0.046***	0.007	−0.050***	0.006
Log of vehicle kilometers × Log of material price	0.039***	0.006	0.032***	0.005
Log of vehicle kilometers × Log of fixed asset	−0.031	0.031	−0.026	0.032
Log of vehicle kilometers × Time trend	0.000	0.003	−0.004**	0.002
Log of load factor × Log of wage	−0.042***	0.010	—	—
Log of load factor × Log of material price	0.015*	0.008	—	—
Log of load factor × Log of fixed asset	0.028	0.039	—	—
Log of load factor × Time trend	−0.003	0.004	—	—
Log of wage × Log of material price	−0.053***	0.009	−0.074***	0.008
Log of wage × Log of fixed asset	0.052***	0.004	0.044***	0.004
Log of wage × Time trend	0.000	0.001	0.001	0.001
Log of material price × Log of fixed asset	−0.049***	0.004	−0.041***	0.003
Log of material price × Time trend	−0.001	0.001	−0.002	0.001
Log of fixed asset × Time trend	0.001	0.002	0.003**	0.001
Constant term	−0.429**	0.189	−0.950***	0.121
Hedonic parameter:				
Log of average number of vehicles	—	—	0.084	0.230
Log of load factor	—	—	0.276**	0.125
Log of average number of tracks	—	—	−1.504***	0.283
Log of non-rail-pass passenger ratio	—	—	−0.976***	0.261
Log of number of vehicle types	—	—	0.221**	0.089
R-squared:				
Variable cost function	0.994		0.994	
Labor cost share function	0.450		0.505	
Material cost share function	0.560		0.582	

Notes: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The number of observations is 356. Standard errors in the hedonic model are robust for the specification. The variable cost function includes company-level individual effects: a dummy variable for each company, except the first company, is included as an independent variable.

Table 3.4: Correlation Matrix among Residuals of Functions of the Generic Model

	Cost	Labor cost share	Material cost share
Variable costs	1.000	——	——
Labor cost share	0.167	1.000	——
Material cost share	−0.141	−0.881	1.000

expressed as follows:

$$\begin{aligned} RTD_{it}^{G} &= \frac{1 - \partial \ln c_{it} / \partial \ln k_{it}}{\partial \ln c_{it} / \partial \ln y_{it}^{VKM} + \partial \ln c_{it} / \partial \ln q_{2it}} \\ &= \{1 - (C + CC \ln k_{it} + AC_1 \ln y_{it}^{VKM} + AC_2 \ln q_{2it} + \textstyle\sum_{m=1}^{2} BC_m \ln w_{mit}^{*} \\ &\quad + CDt)\} / (A_1 + AA_{11} \ln y_{it}^{VKM} + AA_{12} \ln q_{2it} + \textstyle\sum_{m=1}^{2} AB_{1m} \ln w_{mit}^{*} + AC_1 \ln k_{it} \\ &\quad + AD_1 t + A_2 + AA_{22} \ln q_{2it} + AA_{12} \ln y_{it}^{VKM} + \textstyle\sum_{m=1}^{2} AB_{2m} \ln w_{mit}^{*} + AC_2 \ln k_{it} \\ &\quad + AD_2 t), \end{aligned} \tag{3.14}$$

$$\begin{aligned} RTD_{it}^{H} &= \frac{1 - \partial \ln c_{it} / \partial \ln k_{it}}{\partial \ln c_{it} / \partial \ln \psi_{it}} \\ &= \frac{1 - \left\{C + CC \ln k_{it} + AC \left(\ln y_{it}^{VKM} + \sum_{r=1}^{5} \Phi_r \ln q_{rit}\right) + \sum_{m=1}^{2} BC_m \ln w_{mit}^{*} + CDt\right\}}{A + AA \left(\ln y_{it}^{VKM} + \sum_{r=1}^{5} \Phi_r \ln q_{rit}\right) + \sum_{m=1}^{2} AB_m \ln w_{mit}^{*} + AC \ln k_{it} + ADt}. \end{aligned} \tag{3.15}$$

See Caves et al. (1984, 1985) and Harada (2016) for details. Substituting the estimates into the parameters of above equations, we obtain predicted values of the RTD. The RTD for both models are greater than unity for all observations. The sample mean of the predicted RTD from the generic model is 2.364, and that from the hedonic model is 3.330.

3.7 Discussion

3.7.1 Cost System

The estimation results of the cost system are as follows. First, the goodness of fit and the consistency with economic theory are good for both models. In particular, the R-squared values of the variable cost functions are quite high, and the monotonicity and concavity conditions are satisfied at the approximation point, sample mean, and for most observations. Second, the disturbance terms are highly correlated with each other. Thus, using an SUR estimation is supported because the correlation coefficient shows a high negative correlation between the residuals of the two input share functions. Finally, the output characteristics may affect railroads' variable costs. Here, the hedonic model might be preferable because the coefficients of some output characteristics show statistical significance in the hedonic model.

3.7.2 Intensity of Returns to Density

As mentioned in Section 3.6, the predicted RTD is larger than unity for all observations. This indicates the presence of EOD (increasing RTD) in Japanese regional small and medium-sized passenger railroad companies. Furthermore, the sample mean of the RTD calculated from the hedonic model is larger than that of the generic model. This implies that the output characteristics might affect the RTD. The RTD of 3.33, the sample mean of the RTD predicted from the hedonic model, indicates that a 1% increase in all inputs and, thus, in total costs causes a 3.33% increase in output, with the network size held constant.

The results also suggest that the fixed costs of all regional railroad companies in this study might be large, relative to their output. As explained in Sections 3.2 and 3.3, railroad companies with EOD (increasing RTD) can reduce their average costs by increasing their vehicle kilometers. However, this option is not available in Japan owing the decrease in passenger numbers, as mentioned in Section 3.3. Therefore, in order to improve their financial conditions, their fixed assets might need to be reduced in the long term by, for example, removing tracks or rolling stocks that are no longer being used.

Figure 3.1 plots the RTD for all observations against vehicle kilometers. For the RTD calculated from the generic model, there is a positive relationship between

RTD and vehicle kilometers: railroad companies with high vehicle kilometers have a greater RTD than those with fewer vehicle kilometers. As explained in Section 3.1, the relationship between output and RTD is usually negative because the additional quantity of inputs (and total costs) required to increase output increases with the output, resulting in a lower RTD. However, for the RTD calculated from the hedonic model, a positive relationship is not evident. Furthermore, the RTD from the hedonic model is greater than that from the generic model, especially for companies with fewer than 5,000,000 vehicle kilometers. In contrast, for companies with more than 15,000,000 vehicle kilometers, the RTD from the hedonic model is smaller than that from the generic model. Because there is a difference between the values of the RTD generated by the hedonic and generic models for some observations, output characteristics might affect the RTD.

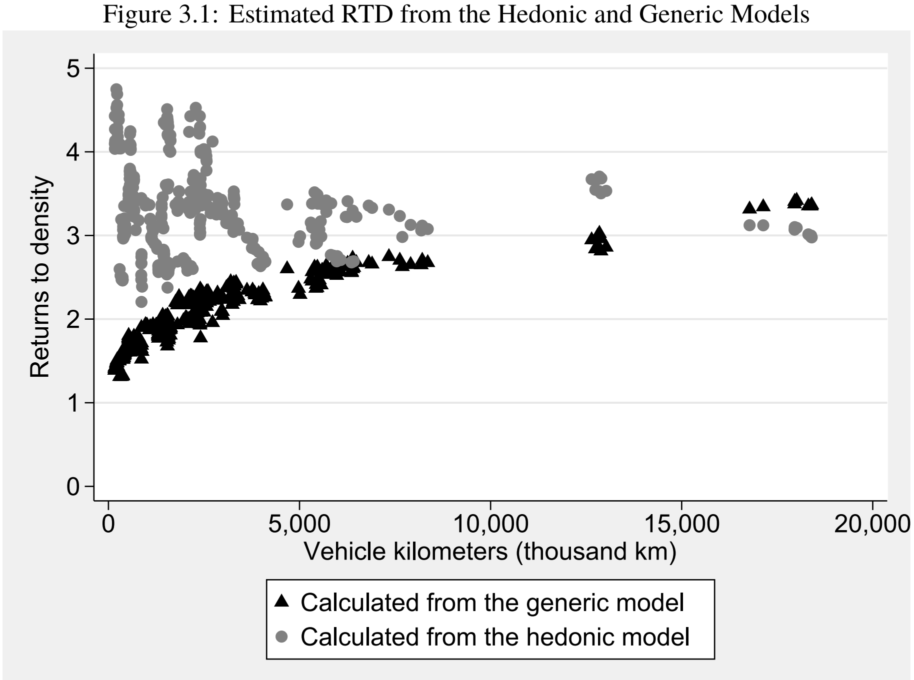
3.7.3 Factors that Affect RTD

In this section, we discuss which output characteristics affect the RTD of railroad companies. This discussion is based on the RTD predicted by the hedonic model only, because some output characteristics may affect the RTD, and the hedonic model, which accounts for output characteristics, is preferable, as described in the previous section. Table 3.5 presents the correlation matrix for the five output characteristics and the predicted RTD. The correlation coefficients between the RTD from the hedonic model and each of output characteristics are presented in the last row of the table. As shown, the RTD from the hedonic model is high when the number of tracks is large and when the railroad company transports a high proportion of non-rail-pass passengers. The correlation coefficient between the average number of tracks shown in the fourth column of Table 3.5 and the RTD from the hedonic model is the highest (0.466). Furthermore, the coefficient between the non-rail-pass passenger ratio shown in the fifth column of Table 3.5 and the RTD from the hedonic model is the second highest (0.415).

However, we cannot see a strong relationship between the average number of tracks and the RTD (see Figure 3.2). This figure presents a scatter plot of the RTD from the hedonic model against the average number of tracks, and a fitted line estimated by regressing the RTD on the average number of tracks. Although the fitted line has an upward slope, it is not clear that there is positive linear relationship.

In contrast, the non-rail-pass passenger ratio shows a clearer correlation with RTD

Figure 3.1: Estimated RTD from the Hedonic and Generic Models



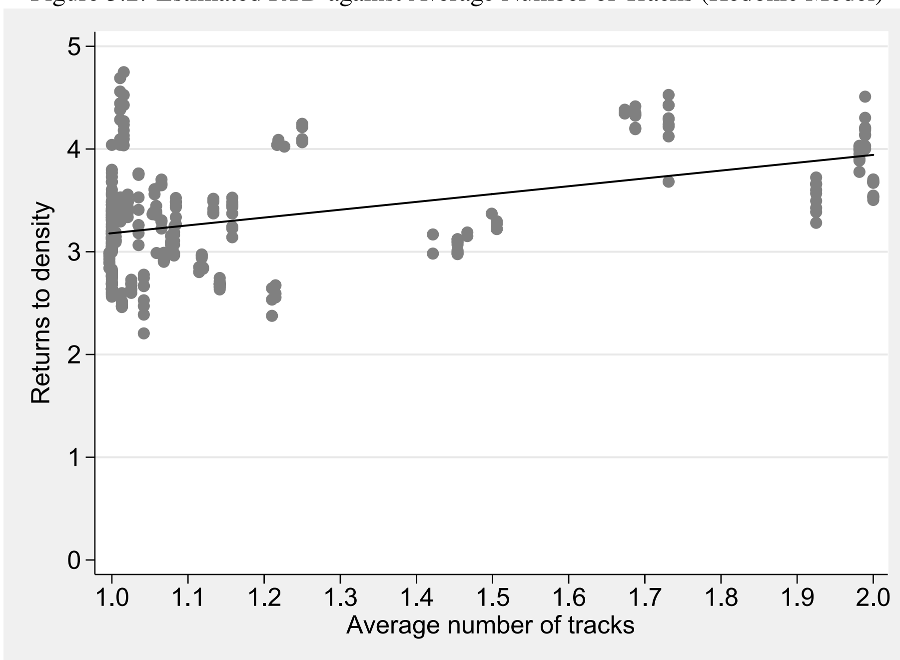
Source: Author's diagram using Annual Rail Statistics and Domestic Corporate Goods Price Index data.

Table 3.5: Correlation Matrix for the Output Characteristics and RTD

	Average number of vehicles	Load factor	Average number of tracks	Non-rail-pass passenger ratio	Number of vehicle types	RTD from generic model	RTD from hedonic model
Average number of vehicles	1.000	—	—	—	—	—	—
Load factor	**0.861**	1.000	—	—	—	—	—
Average number of tracks	−0.167	−0.127	1.000	—	—	—	—
Non-rail-pass passenger ratio	0.242	0.270	0.247	1.000	—	—	—
Number of vehicle types	**0.463**	0.356	−0.246	−0.060	1.000	—	—
RTD from generic model	**0.678**	**0.661**	0.283	0.123	**0.418**	1.000	—
RTD from hedonic model	−0.384	−0.350	**0.466**	**0.415**	−0.384	−0.143	1.000

Note: Bold figures indicate that (the absolute values of) the correlation coefficients are greater than 0.4.

Figure 3.2: Estimated RTD against Average Number of Tracks (Hedonic Model)



Source: Author's diagram using Annual Rail Statistics and Domestic Corporate Goods Price Index data.

Notes: The fitted regression line is defined as

$$\underset{(0.065)}{\text{RTD} = 0.762} \times \text{Average number of tracks} + \underset{(0.084)}{2.418}, \; R^2 = 0.217.$$

Heteroskedasticity-robust standard errors are shown in parentheses.

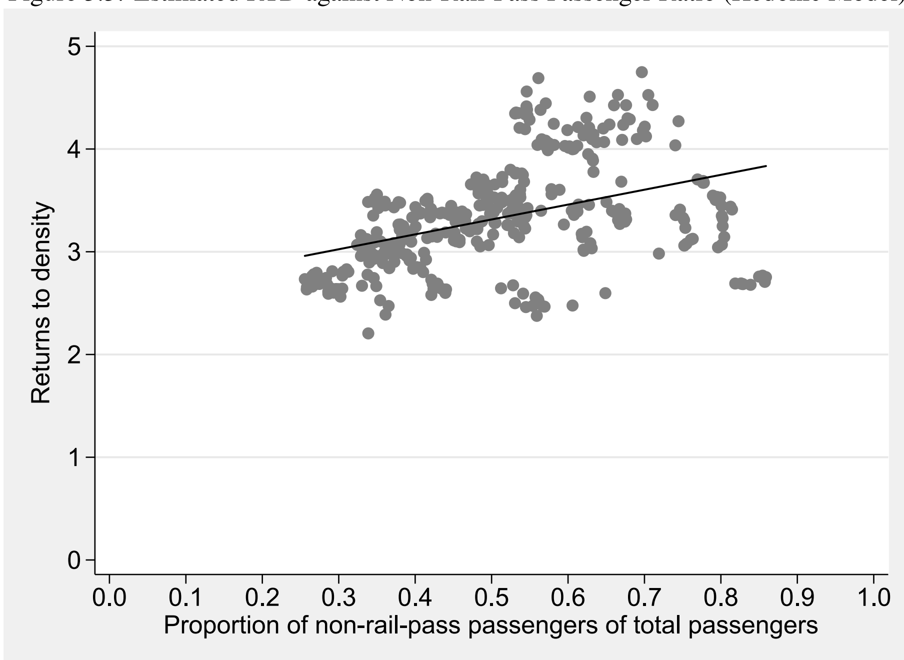
than does the average number of tracks (Figure 3.3). This figure presents a scatter plot of the RTD from the hedonic model against the non-rail-pass passenger ratio, and the fitted line is estimated by regressing the RTD on the non-rail-pass passenger ratio. The (regression) coefficient of the non-rail-pass passenger ratio (1.449) shown in the note to Figure 3.3 is obviously larger than that of the average number of tracks (0.762) shown in the note to Figure 3.2. Therefore, the non-rail-pass passenger ratio might be a major factor affecting the RTD of the railroad companies. We discuss this factor below.

Whether a company transports commuting passengers might be related to the RTD. Figure 3.4 plots the RTD from the generic model for all observations against vehicle kilometers, with two types of marks showing the different ranges of the proportion of passengers who do not use a rail pass of the total number of passengers. In addition, Figure 3.5 plots the RTD from the hedonic model for all observations against vehicle kilometers, again using two types of marks for different ranges of the non-rail-pass passenger ratio. The RTD calculated from the hedonic model for railroad companies that transport a high proportion of non-rail-pass passengers tends to be greater than that calculated from the generic model (Figures 3.4 and 3.5). Railroad companies with a low non-rail-pass passenger ratio transport mainly commuting passengers. In contrast, railroad companies with a high non-rail-pass passenger ratio transport mainly other types of passengers (e.g., tourists, shoppers, outpatients). Thus, Figure 3.5 suggests that railroad companies that transport mainly commuters may have a lower RTD than those that transport mainly other types of passengers.

The reason for this result may be that railroad companies that transport commuting passengers use many of their train vehicles in peak time. Hence, their additional total costs might be higher if they increase their vehicle kilometers. When vehicle kilometers increase, the decrease in the average costs of the railroad companies that transport commuters might be smaller than that of companies that transport other types of passengers. Therefore, the RTD of the former companies is lower than that of the latter companies, even though their vehicle kilometers are similar.

Our findings suggest the following policy implication: reducing railroad companies' facilities might improve their performance, especially in the case of companies that transport mainly non-commuting passengers. As explained in Sections 3.1 and 3.3, railroad companies can reduce their average costs by increasing their vehicle kilometers or by reducing their facilities when they have an increasing RTD. However, the decreasing number of passengers using Japanese regional small and medium-sized railroads means reducing their facilities is an appropriate way to reduce their average

Figure 3.3: Estimated RTD against Non-Rail-Pass Passenger Ratio (Hedonic Model)

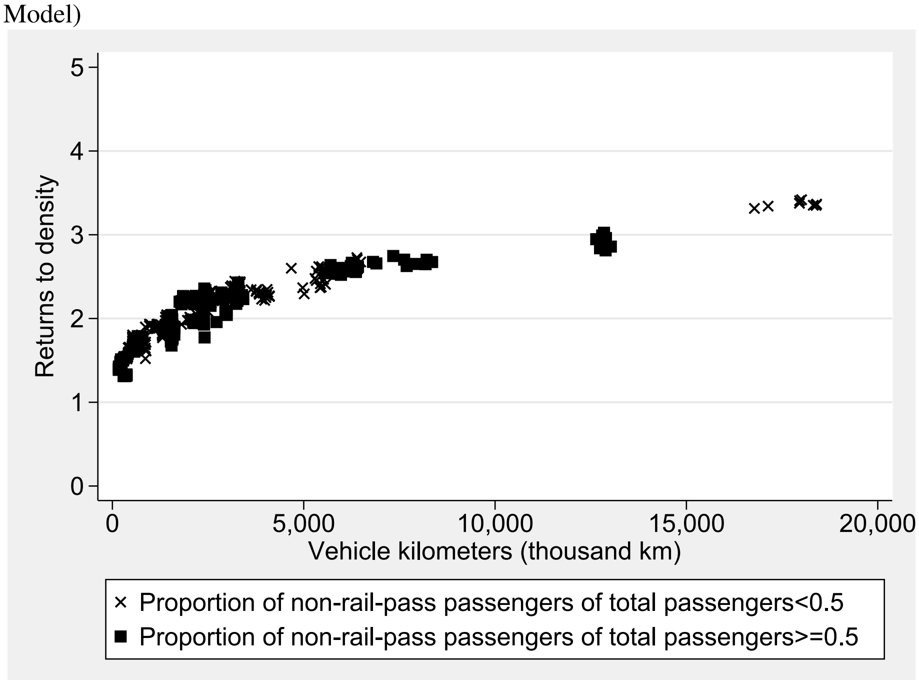


Source: Author's diagram using Annual Rail Statistics and Domestic Corporate Goods Price Index data.
Notes: The fitted regression line is defined as

$$\underset{(0.195)}{\text{RTD} = 1.449} \times \text{Non-rail-pass passenger ratio} + \underset{(0.089)}{2.590}. \quad R^2 = 0.172,$$

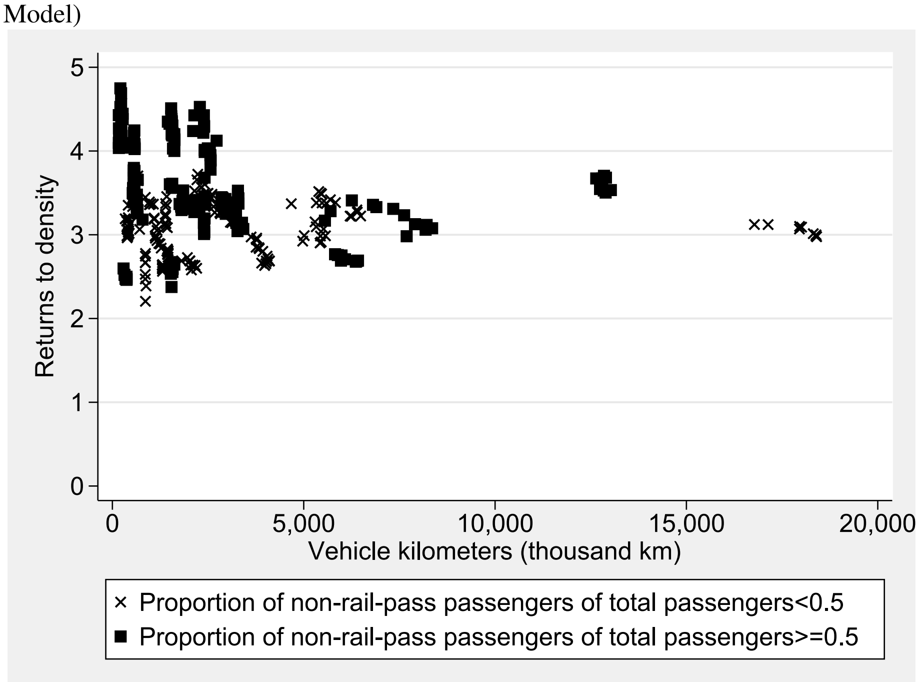
Heteroskedasticity-robust standard errors are shown in parentheses.

Figure 3.4: Estimated RTD for Different Ranges of the Non-Rail-Pass Ratio (Generic Model)



Source: Author's diagram using Annual Rail Statistics and Domestic Corporate Goods Price Index data.

Figure 3.5: Estimated RTD for Different Ranges of the Non-Rail-Pass Ratio (Hedonic Model)



Source: Author's diagram using Annual Rail Statistics and Domestic Corporate Goods Price Index data.

costs. The empirical results indicate that railroad companies that transport mainly non-commuters may have a higher RTD than those that transport commuters. Hence, reducing the tracks or rolling stocks that are no longer being used would reduce the average costs and improve the companies' financial situation and long-run viability, especially in the case of those that transport non-commuters.

3.8 Conclusions

The issue of EOD in the railroad industry is an important research topic. Using panel data on Japanese regional small and medium-sized passenger railroad companies, we calculated the RTD, an indicator of EOD, for these companies. We found that EOD (increasing RTD) exists for these railroad companies, and that companies with a high proportion of non-rail-pass passengers have a greater RTD than those with a low proportion of non-rail-pass passengers do, when accounting for output characteristics.

These empirical results suggest as follows. First, the fixed costs of all regional railroad companies in this study might be large relative to their output. Thus, facilities that are no longer being used might need to be reduced in the long term in order to improve their financial conditions, given the reduction in the number of passengers. Second, whether a railroad company transports mainly commuting passengers might be a factor that affects its RTD. In other words, the RTD of railroad companies that transport mainly commuting passengers is lower than that of railroad companies that transport mainly other types of passengers, such as tourists. Therefore, reducing useless facilities (e.g., rolling stocks or tracks) would improve a railroad company's performance and its long-run viability, especially in the case of railroad companies that transport non-commuting passengers.

This study has several limitations. First, we cannot say that a railroad company will reduce (and finally exhaust) its RTD when the number of commuters or students along its lines increase. This is because we compared each company's RTD in a cross-sectional analysis because our panel data cover a relatively short period (nine years). However, the use of some of the inputs of the railroad companies in Japan have not changed significantly for a long time. Hence, a significant time-series correlation between the output and RTD of a company may not be observable, even if we analyze longer-term panel data. Second, in order to obtain better estimates of the cost system, we omitted some companies from the sample. Therefore, the results may not be generalizable for

Japanese regional small and medium-sized passenger railroad companies. We omitted certain companies because we obtained a positive coefficient on the capital variable in the variable cost function when we included companies that use diesel and the third-sector railroad companies that operate *heiko zairaisen* in the sample. We also obtained a variable cost function that is not concave with respect to input prices when we included these companies.[5] Finally, the cost function does not satisfy the monotonicity condition with respect to capital for some observations, even though we limited the companies in the analysis. Another approach to improve this issue, other than limiting the sample, may be to estimate capital stock using the perpetual inventory method and using it as the capital variable. However, as mentioned in Section 2.5 in Chapter 2, constructing the capital stock variable is difficult, owing to the lack of data. Because of these limitations, we need to carefully interpret the results. Nevertheless, this study contributes to evaluating the RTD of Japanese regional small and medium-sized railroad companies and identifying those factors affecting their RTD.

[5]When including diesel companies in the sample, we converted oil consumption to electricity consumption using the method same as in Mizutani and Uranishi (2007) and Mizutani et al. (2009).

Chapter 4

Long-run Impact of Track Improvements on Productivity

4.1 Introduction

Japanese regional small and medium-sized railroad companies have improved their track equipment, for example, by installing heavy rails and concrete sleepers. According to the data adopted in this study, between FY 1994 and FY 2013, about 72% of the railroad companies replaced light rails with heavy rails (weighing 50 kg or more per meter; hereafter, "50 kg/m and over rails") and wooden sleepers with concrete sleepers. Installing heavy rails and concrete sleepers can reduce the frequency of track maintenance (Japan Railway Construction, Transport and Technology Agency, 2008a,b). Thus, replacing this equipment can increase the productivity of railroad companies.

In Japan, regional small and medium-sized passenger railroad companies face high facility costs, including high track maintenance costs. In FY 2011, facility costs accounted for about 45% of total costs (Kajimaya and Tokutake, 2013). Thus, we need to find ways to reduce these costs, particularly because they pose a major obstacle to operations. One possible solution to the problem of high facility costs is track improvements. Therefore, this is one of the ways in which railroad companies can increase their productivity.

As explained in the previous chapter, Japanese regional small and medium-sized passenger railroad companies also face a reduction in the number of passengers owing to the reduction of the population along their routes. Therefore, this is one of the factors that is reducing railroad companies' productivity.

Hence, there are at least two possible factors that may affect railroad companies' productivity: the reduction in the number of passengers (reduces productivity) and track improvements (increases productivity). This means that installing heavy rails and concrete sleepers may increase (or relieve the decrease in) the productivity of railroad companies, despite the reduction in the number of passengers. The installation of heavy rails and concrete sleepers is subsidized by the national and local governments. Therefore, if track improvements can increase companies' productivity by reducing their costs, then related investments and government subsidies may be significant.

However, it takes time (e.g., 10 years) to reduce costs or to increase productivity after installing concrete sleepers (Board of Audit of Japan, 2016). This may be because doing so requires that track staff acquire experience and skill. Hence, understanding how long it takes for railroad companies' productivity to improve after track improvements, and the extent of this improvement in the long-run is significant from the perspectives of railroad companies' practice (investment behavior) and government policy (subsidization).

Several studies have explored the total factor productivity (TFP) of railroads. For example, railroads' TFP was found to be associated with a technology and a type of employee in India. Bogart and Chaudhary (2013) used Indian railroad data prior to World War I to show that the adoption of gas lighting, a new technology in India at the time, increased railroads' TFP. Deshpande and Weisskopf (2014) also studied Indian railroads, using 1980–2002 data, and revealed that the ratio of employees who belong to groups that have been historically discriminated against was positively correlated with railroads' TFP.

With regard to track maintenance costs of railroads, several researchers have examined the elasticity of track maintenance costs with respect to transport volume or marginal maintenance cost (Johansson and Nilsson, 2004; Wheat and Smith, 2008; Gaudry et al., 2016; Odolinski and Nilsson, 2017), as well as the impact of competitive tendering on maintenance costs (Odolinski and Smith, 2016). Some of these studies regressed maintenance costs on factors such as track quality (rails' heaviness, sleeper types, whether rails are welded, etc.). However, they obtained inconsistent results.

The track maintenance costs of railroads with high track quality were found to be significantly low in Sweden and Finland (Johansson and Nilsson, 2004), but significantly high in Britain (Wheat and Smith, 2008). In contrast, Odolinski and Smith (2016) and Odolinski and Nilsson (2017) found no significant relationship between track quality and maintenance costs in Sweden.

Although these studies are related to a railroad's productivity or track maintenance costs, few researchers have examined how long it takes for track improvements to increase productivity or the long-run impacts of track improvements on productivity. To fill this gap, we empirically study these issues. Annual data on railroads in Japan enable us to examine these issues because the data include adoption levels of each rail and sleeper type for each railroad company. We estimate the production function of Japanese regional small and medium-sized passenger railroad companies under several different assumptions. Next, we predict the annual TFP of each railroad company and examine the long-run elasticity of TFP with respect to track improvements by estimating a distributed lag model, regressing TFP on current and past adoption rates of improved tracks.

The empirical analysis shows that a 1% increase in the adoption rate of concrete sleepers every year may increase (or ease the reduction in) TFP by 1.554% after 11 years. This is probably because installing concrete sleepers reduces the frequency of track maintenance and the usage of trackmen. In contrast, we could not find a significant impact of an increase in the adoption rate of 50 kg/m and over rails on TFP. This is probably because the tolerance change of replacing light rails with heavier rails is smaller than that of replacing wooden sleepers with concrete sleepers.

The remainder of this chapter is structured as follows. Section 4.2 discusses the characteristics of track improvements in Japan. Section 4.3 describes the econometric models used as estimation methods. Section 4.4 explains the data employed in the study. Then, Sections 4.5 and 4.6 present and discuss the estimation results, respectively. Finally, Section 4.7 concludes the chapter.

4.2 Track Improvements in Japanese Railroads

Train operations and the infrastructure of most Japanese railroad companies are vertically integrated (Mizutani et al., 2009). Therefore, most railroad companies own track facilities, including rails and sleepers, which they need to maintain and improve.

In Japan, the heaviness of rails is measured by the weight of rail per meter. Some companies use rails with a weight of less than 30 kg/m, while others use rails with a weight greater than 60 kg/m. Replacing light rails with heavier rails not only strengthens the rails and makes them safer, but also reduces the frequency of track maintenance and labor costs (Japan Railway Construction, Transport and Technology Agency, 2008a). Thus, heavy rails could contribute to increasing companies' TFP.

There are also various types of sleepers. Originally, many companies used wooden sleepers, although an increasing number of companies have replaced these with concrete sleepers. The consequences of doing so are identical to those of introducing heavy rails (Japan Railway Construction, Transport and Technology Agency, 2008b). Hence, concrete sleepers may also increase companies' TFP.

The replacement of rails and sleepers with heavier options is particularly advanced in Japanese regional small and medium-sized passenger railroad companies. The data employed in this study demonstrate that out of 32 railroad companies, 29 (91%) increased their use of either 50 kg/m and over rails or concrete sleepers during FY 1994–2013. Of these 29 companies, 23 companies increased their adoption rates of both options, three companies increased their use of 50 kg/m and over rails only, and the remaining three companies increased their use of concrete sleepers only. The average adoption rates per fiscal year also increased from FY 1994 to FY 2013 for both options. Figure 4.1 shows the average adoption rates of both types of equipment. As shown, the average adoption rate of 50 kg/m and over rails and concrete sleepers increased by about 21% and 8%, respectively, during the period.

4.3 Models and Methods

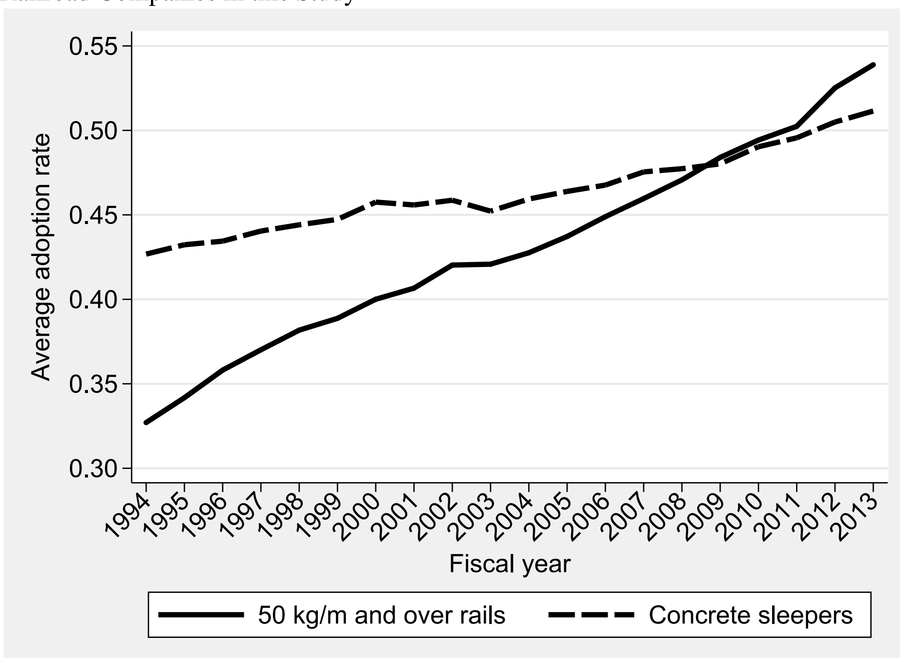
4.3.1 Production Function

Here, we estimate the production function in order to predict TFP. Following Bogart and Chaudhary (2013) and Deshpande and Weisskopf (2014), we specify the function as a gross revenue Cobb–Douglas production function for company i in year t:

$$\ln y_{it}^{PKM} = \beta_{P0} + \beta_{PK} \ln k_{it} + \beta_{PM} \ln m_{it} + \beta_{PL} \ln l_{it} + \omega_{it} + \eta_{it}, \tag{4.1}$$

where y_{it}^{PKM} is the output (passenger kilometers), k_{it} is capital, m_{it} is an intermediate input, l_{it} is labor, ω_{it} is productivity, and η_{it} is an error term. While a company

Figure 4.1: Changes in the Average Adoption Rates of Improved Tracks of the 32 Railroad Companies in this Study



Source: Author's diagram using Annual Rail Statistics data.

can observe ω_{it}, econometricians cannot do so. In addition, neither a company nor econometricians can observe η_{it}. Thus, we assume η_{it} has no correlation with the three inputs.

The variables used in this production function, y_{it}^{PKM}, k_{it}, l_{it}, and m_{it}, are same as those of the distance function (2.5) in Section 2.4.

4.3.2 Estimation Methods

We estimate (4.1) by applying the following methods: ordinary least squares (OLS), least square dummy variables (LSDV), and the method proposed by Ackerberg et al. (2015), called the Ackerberg–Caves–Frazer (ACF) method.

First, we apply the OLS method by assuming that the disturbance term of the function is uncorrelated with all independent variables, and allowing each company's productivity to be time-variant. The disturbance term of (4.1) is $\omega_{it} + \eta_{it}$ and the independent variables of the model are $\ln k_{it}$, $\ln m_{it}$, and $\ln l_{it}$. Therefore, the productivity that is observable to a company, but unobservable to econometricians, ω_{it}, is assumed to have no correlation with all usage of inputs.

Second, we conduct the following LSDV estimation by assuming that productivity is time-invariant: $\omega_{it} = \omega_i$. This estimation allows time-invariant productivity, ω_i, to be correlated with the usage of inputs. In this estimation, we include each company's dummy variables, except for those of the first company. These dummy variables capture each company's time-invariant effects that are regarded as productivity, ω_i.

In contrast to the OLS and LSDV methods, the ACF method considers both the possibility that productivity, ω_{it}, is correlated with inputs and that it is time-variant. This paragraph explains why productivity may be correlated with inputs. In the production function, the causality between the inputs and output could move in both directions (i.e., from inputs to output, and vice versa). This phenomenon, called simultaneity, is one of the endogeneity issues. Simultaneity can occur for the following reasons. Because a company can observe its productivity, it may adjust its input levels depending on contemporary productivity. For example, when productivity is high, the company may increase the number of workers and its intermediate inputs (e.g., energy for vehicles) and, thus, $\ln l_{it}$ and $\ln m_{it}$ would be correlated with ω_{it}. Furthermore, if the company makes a large investment when productivity is high, then capital in the next year increases, although gradually, and $\ln k_{i,t+1}$ is correlated with ω_{it}. In this case, if ω_{it} has a serial correlation, then $\ln k_{it}$ and ω_{it} are correlated. Therefore, if this is true, the

OLS estimator of the coefficients in (4.1) may be biased because of the simultaneity; that is, the inputs and productivity are correlated.

Next, we describe the procedure used to estimate the production function (4.1) using the ACF method. The procedure has two stages.

In the first stage, we separate productivity from the disturbance term for the production function. To do so, we assume that intermediate input demand is a function of capital, labor, and productivity:

$$\ln m_{it} = \tilde{f}(\ln k_{it}, \ln l_{it}, \omega_{it}). \tag{4.2}$$

We further assume that this function is monotonically increasing in ω_{it}. Thus, we invert (4.2) with respect to ω_{it}:

$$\omega_{it} = \tilde{f}^{-1}(\ln k_{it}, \ln m_{it}, \ln l_{it}). \tag{4.3}$$

Now, the productivity ω_{it} is a function of $\ln k_{it}$, $\ln m_{it}$, and $\ln l_{it}$. Substituting (4.3) into (4.1), we can rewrite the production function as

$$y_{it}^{PKM} = \tilde{\phi}(\ln k_{it}, \ln m_{it}, \ln l_{it}) + \eta_{it}, \tag{4.4}$$

where

$$\begin{aligned}\tilde{\phi}(\ln k_{it}, \ln m_{it}, \ln l_{it}) = \beta_{P0} + \beta_{PK} \ln k_{it} + \beta_{PM} \ln m_{it}\\ + \beta_{PL} \ln l_{it} + \tilde{f}^{-1}(\ln k_{it}, \ln m_{it}, \ln l_{it}).\end{aligned} \tag{4.5}$$

The disturbance term of (4.4) is only η_{it}, which has no correlation with the inputs. However, the functional form of $\tilde{\phi}(\ln k_{it}, \ln m_{it}, \ln l_{it})$ is unknown. Thus, we approximate this using the high-order polynomial in $(\ln k_{it}, \ln m_{it}, \ln l_{it})$. We can estimate (4.4) using the OLS method and, accordingly, obtain $\hat{\tilde{\phi}}(\ln k_{it}, \ln m_{it}, \ln l_{it})$ as the estimates of $\tilde{\phi}(\ln k_{it}, \ln m_{it}, \ln l_{it})$. Note that none of coefficients on inputs are estimated in this stage.

In the second stage, we remove the correlation between capital and the disturbance term before estimating the production function. As the important assumption to remove this correlation, we assume that productivity follows a first-order Markov process:

$$\begin{aligned}\omega_{it} &= E\left[\omega_{it} \mid \omega_{i,t-1}\right] + \xi_{it}\\ &= \tilde{g}(\omega_{i,t-1}) + \xi_{it}\\ &= \tilde{g}\left(\tilde{\phi}(\ln k_{i,t-1}, \ln m_{i,t-1}, \ln l_{i,t-1}) - \beta_{P0}\right.\\ &\qquad \left. - \beta_{PK} \ln k_{i,t-1} - \beta_{PM} \ln m_{i,t-1} - \beta_{PL} \ln l_{i,t-1}\right) + \xi_{it},\end{aligned} \tag{4.6}$$

where ξ_{it} is an innovation for productivity that is uncorrelated with $\omega_{i,t-1}$ and, thus, $\ln k_{it}$. The third equals sign of (4.6) comes from (4.3) and (4.5). Substituting (4.6) into (4.1), and replacing $\tilde{\phi}(.)$ with its estimate from the first stage, $\hat{\tilde{\phi}}(.)$, the production function is rewritten as

$$\begin{aligned}\ln y_{it}^{PKM} = \beta_{P0} + \beta_{PK} \ln k_{it} + \beta_{PM} \ln m_{it} + \beta_{PL} \ln l_{it} + \tilde{g}\Big(&\hat{\tilde{\phi}}(\ln k_{i,t-1}, \ln m_{i,t-1}, \ln l_{i,t-1}) \\ &- \beta_{P0} - \beta_{PK} \ln k_{i,t-1} - \beta_{PM} \ln m_{i,t-1} - \beta_{PL} \ln l_{i,t-1}\Big) + \widehat{\xi_{it} + \eta_{it}},\end{aligned} \tag{4.7}$$

where $\widehat{\xi_{it} + \eta_{it}} = \tilde{g}(\tilde{\phi}(.)) - \tilde{g}(\hat{\tilde{\phi}}(.)) + \xi_{it} + \eta_{it}$. The disturbance term of (4.7) is $\widehat{\xi_{it} + \eta_{it}}$. As mentioned previously, the innovation for productivity ξ_{it} has no correlation with $\ln k_{it}$. Thus, the disturbance term in (4.7) is not correlated with $\ln k_{it}$. With regard to intermediate input and labor, we assume that productivity and its innovation in the same year are uncorrelated with the intermediate input in the previous year. Furthermore, $\ln k_{i,t-1}$, $\ln m_{i,t-2}$, and $\ln l_{i,t-2}$ are also assumed to have no correlation with ω_{it} and ξ_{it}. Therefore, we have six instrumental variables, $(\ln k_{it}, \ln m_{i,t-1}, \ln l_{i,t-1}, \ln k_{i,t-1}, \ln m_{i,t-2}, \ln l_{i,t-2})$, and the following moment condition is available:

$$E\left[\left(\widehat{\xi_{it} + \eta_{it}}\right)\begin{pmatrix}\ln k_{it} \\ \ln m_{i,t-1} \\ \ln l_{i,t-1} \\ \ln k_{i,t-1} \\ \ln m_{i,t-2} \\ \ln l_{i,t-2}\end{pmatrix}\right] = 0. \tag{4.8}$$

An estimation using this moment condition (4.8) assumes that companies can optimize (adjust) their labor usage in a year, depending on their current productivity. However, if companies cannot adjust their labor in a year, depending on ω_{it}, we can add $\ln l_{it}$ to the set of instruments (Ackerberg et al., 2015):

$$E\left[\left(\widehat{\xi_{it}+\eta_{it}}\right)\begin{pmatrix}\ln k_{it}\\ \ln m_{i,t-1}\\ \ln l_{it}\\ \ln l_{i,t-1}\\ \ln k_{i,t-1}\\ \ln m_{i,t-2}\\ \ln l_{i,t-2}\end{pmatrix}\right]=0. \tag{4.9}$$

This assumption (labor cannot be adjusted immediately) might be appropriate in industries or countries where the law or the government strictly regulates hiring and firing, or where there are labor market rigidities, such as long-term labor contracts (Ackerberg et al., 2015; Manjón and Mañez, 2016). This situation may occur in the railroad industry in Japan and, thus, the latter moment conditions (4.9) may be appropriate in this study.[1]

Finally, we identify the production function's coefficients on inputs, $(\beta_{PK}, \beta_{PM}, \beta_{PL})$, using the generalized method of moments with the moment conditions (4.8) or (4.9). For details, see Petrin et al. (2004), Ackerberg et al. (2015), and Manjón and Mañez (2016).

The method used to estimate the production function by accounting for simultaneity was proposed by Olley and Pakes (1996), and then later improved upon by Levinsohn and Petrin (2003).[2] Their techniques estimate the coefficient of labor in the first stage, and then those of the others in the second. However, the coefficient of labor cannot be identified separately from the others because of the functional dependence problem (Ackerberg et al., 2015). Thus, the ACF method was proposed as a way to avoid this problem.

Among the three techniques that handle simultaneity, the Levinsohn–Petrin (LP) and ACF methods can be applied to our data. However, the Olley–Pakes (OP) method cannot be applied, because, in contrast to the LP and ACF methods, it requires companies' equipment investment data, which are not available for Japanese railroad companies. As explained in footnote 3 of Chapter 2, the estimation reports the investments of certain

[1]This situation is also true in European countries such as Spain (Manjón and Mañez, 2016).

[2]Bogart and Chaudhary (2013) and Deshpande and Weisskopf (2014) estimated the railroad production function by applying the Levinsohn–Petrin method.

companies as negative. Similarly to the OP method, the LP method suffers from the functional dependence problem, as mentioned in the former paragraph. Therefore, we use the ACF method for the estimation that considers simultaneity.

4.4 Data

This chapter adopts unbalanced panel data for the same companies and period as those in Chapter 2: a total of 45 small and medium-sized railroad companies with routes in Japanese regional areas during the period FY 1994–2013. Based on the explanation in Section 4.1, observing the long-run impact of track improvements requires long-term data. Therefore, we examine a 20-year period. Of the 45 railroad companies, 32 existed in the period from FY 1994 to FY 2013, as mentioned in Section 2.5. Thus, the data sources are also the same as those in Chapters 2 (and 3): the "Annual Rail Statistics," published by the Ministry of Land, Infrastructure, Transport and Tourism, and the "Domestic Corporate Goods Price Index, All Commodities," published by Bank of Japan.

This thesis does not examine large-scale railroad companies or those in urban areas. Including these companies in our sample has no real significance in this chapter because they had already installed heavy rails and concrete sleepers on most of their lines before FY 1994.

In addition to the variables used in Chapter 2, we define a further two variables (50 kg/m and over rails, and concrete sleepers) for the adoption rates in order to estimate the distributed lag model (described in Section 4.5) and to investigate the impact of track improvements. The idea of using adoption rate variables is based on Bogart and Chaudhary (2013).

These variables also have several missing values, even when companies existed during the study period. Similarly to the former chapters, we substitute the mean values of the previous and subsequent years for the missing values.

Furthermore, some categorizations into rail types after a certain year were apparently incorrect. For example, the Annual Rail Statistics reports that Izukyu Company Limited (Co., Ltd.) had laid "40–50 kg/m" rails along a distance of 45.7 kilometers since FY 2009, which is obviously an error, because the same length (45.7 kilometers) is recorded against the "50–60 kg/m" rail type until FY 2008 (replacing heavier rails for the whole 45.7 kilometers section with lighter rails within a single year is unrealistic). Upon

Table 4.1: Descriptive Statistics for the Distributed Lag Model for TFP

Variable	Mean	Median	Minimum	Maximum	Standard deviation
50 kg/m rail ratio	0.43	0.34	0.00	1.00	0.37
Concrete sleeper ratio	0.44	0.45	0.00	0.97	0.33

Note: The number of observations is 785.

Table 4.2: Definitions of Variables for Distributed Lag Model for TFP

Variable	Definition
50 kg/m rail ratio	The length of 50 kg/m and over rails divided by total track length
Concrete sleeper ratio	The length of tracks for concrete sleepers divided by total track length for all sleeper types

inquiry at the office of Izukyu Co., Ltd., we found that this is an error. Therefore, we followed the previous years' classification, even after FY 2009, for the "50–60 kg/m" rails.

Tables 4.1 and 4.2 present the descriptive statistics and definitions of the two adoption rates, respectively. The tables show that the adoption rate of 50 kg/m and over rails in certain years is 0% for certain companies, but 100% for others. With regard to concrete sleepers, the adoption rate is 0% for some, but 97% for others. This chapter also use passenger kilometers, fixed assets, electricity, labor, the passengers' route-use ratio, and the non-rail-pass passenger ratio. Because these variables are common to Chapter 2 and this chapter, see Tables 2.1 and 2.2 in Chapter 2 for the descriptive statistics and definitions of these six variables.

4.5 Empirical Results

4.5.1 Production Function

We estimate the production function (4.1) using four assumptions. The estimation results of the production function are presented in Table 4.3. The second column of this table shows the results of the OLS method, assuming that time-variant productivity is uncorrelated with input usage. The third column presents the results of the LSDV method, under the assumption that productivity is time-invariant and may be correlated with inputs. The fourth column, labeled ACF (1), shows the results of the ACF method, assuming that railroad companies can adjust their labor in a year to respond to the current productivity level. The coefficients from ACF (1) are estimated to satisfy the moment conditions (4.8). The final column, labeled ACF (2), presents the results of the ACF method, assuming that companies cannot adjust their labor in a year based on their current productivity levels. The coefficients from ACF (2) are estimated to satisfy the moment conditions (4.9). Before conducting the ACF (2) assumption method, we edited the ado file for Stata (i.e., `acfest` command) to add the moment condition in which the disturbance term and the contemporary labor variable are orthogonal. Note that constant term cannot be identified by the ACF method.

Table 4.3 reports the following statistical results. First, all three coefficients of the logs of inputs show a positive sign and statistical significance at the 10% significance levels, at least, for all estimations. Thus, the results are consistent with economic theory. Second, the coefficients of the log of fixed assets (capital) are consistently smaller than 0.05 for all estimations, and the coefficient from the LSDV estimation shows the lowest value, even though their signs are positive and significant. This may be attributed to defining the capital variable as fixed assets instead of capital stock, owing to limitations in our data. Third, the coefficients of the logs of the inputs from the LSDV estimation, shown in the third column of Table 4.3, are smaller than those of the other three estimations, especially in the case of the log of electricity. The magnitude of the fixed asset coefficient from the LSDV method (0.026) is about 60% of that of the OLS method (0.043), and the magnitude of the electricity coefficient from the LSDV method (0.286) is less than 40% of that of the other techniques (0.795, 0.789, and 0.741, respectively). This can be attributed to the high autocorrelation of each input, and especially electricity. Ackerberg et al. (2007) mentions that a fixed-effect estimation, such as that of the LSDV method, of the capital coefficient often becomes

Table 4.3: Estimation Results of Production Function

	OLS	LSDV	ACF (1)	ACF (2)
Lof of fixed asset	0.043***	0.026***	0.037***	0.037***
	(0.014)	(0.009)	(0.014)	(0.014)
Log of electricity	0.795***	0.286***	0.789***	0.741***
	(0.038)	(0.065)	(0.135)	(0.111)
Log of labor	0.350***	0.339***	0.385*	0.470***
	(0.038)	(0.053)	(0.209)	(0.078)
Constant term	−3.864***	3.644***	——	——
	(0.392)	(0.952)	——	——
Company-level individual effect	No	Yes	No	No
Year-level time effect	Yes	Yes	No	No
P–value for over-identifying restriction	——	——	0.989	0.998
Number of observations	785	785	695	695

Notes: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. ACF (1) is the estimation assuming that companies can optimize (adjust) their labor usage in a year, depending on their productivity. ACF (2) assumes that companies cannot optimize (adjust) their labor usage within a year, regardless of the productivity. Heteroskedastic robust standard errors are shown in parentheses for the OLS and LSDV methods. The bootstrap arbitrary heteroskedasticity robust standard errors are shown in parentheses for ACF (1) and (2).

unreasonably low. Thus, there is a possibility that the LSDV estimation will not work well in this study. Therefore, we focus on the results from the OLS, ACF (1), and (2) methods below. Fourth, the p-values for over-identifying the restriction for the ACF (1) and (2) estimations, shown in the second from last row, are almost one: thus, we cannot reject the null hypothesis that instruments are uncorrelated with the disturbance term at any conventional significance levels. Thus, the instruments in (4.8) and (4.9) might be valid. Finally, the three coefficients of the logs of the inputs do not vary substantially among the OLS, and ACF (1) and (2) estimations.

4.5.2 TFP

Using the estimates of the production function, we next predict the TFP. According to Petrin et al. (2004) and Bogart and Chaudhary (2013), the log of TFP can be expressed as

$$\ln TFP_{it} = \ln y_{it}^{PKM} - \hat{\beta}_{PK} \ln k_{it} - \hat{\beta}_{PM} \ln m_{it} - \hat{\beta}_{PL} \ln l_{it}, \tag{4.10}$$

where $\hat{\beta}_{PK}$, $\hat{\beta}_{PM}$, and $\hat{\beta}_{PL}$ are estimates for β_{PK}, β_{PM}, and β_{PL}, respectively.

Figure 4.2 plots the changes in the log of TFP predicted by (4.10) using the OLS, and ACF (1) and (2) estimates. Each plotted line is the average log of the TFP of the 32 railroad companies that existed during the period FY 1994–2013. In all three case, the predicted TFP show similar movements: they continued to decrease until FY 2004, and started increasing from FY 2011.

4.5.3 Distributed Lag Model

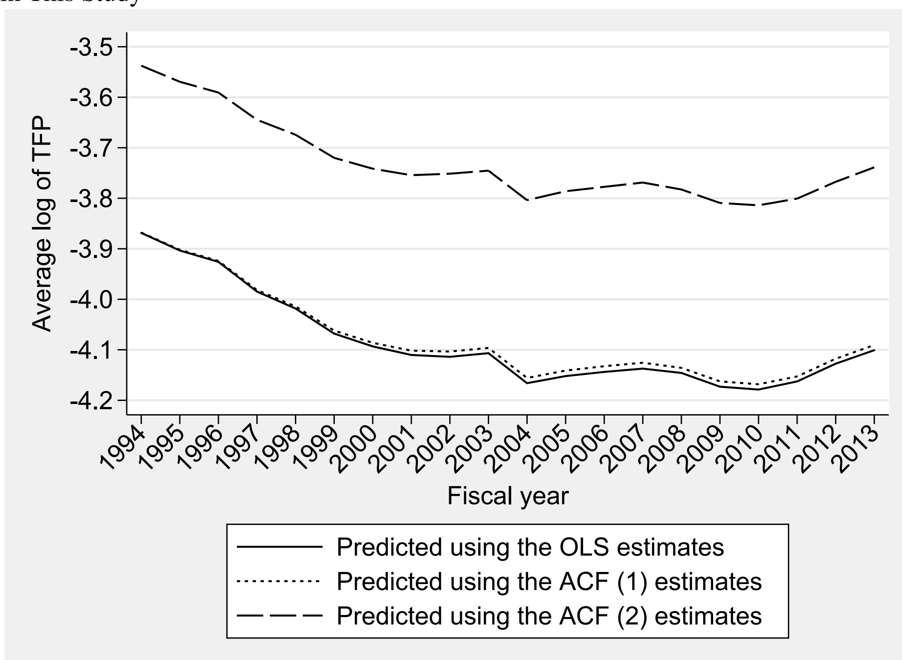
Here, we estimate long-run elasticity (LRE) of TFP with respect to track improvements. As described in Section 4.1, it takes time to reduce costs or to increase productivity after track improvements because employees need experience and skill. To reflect this in the empirical model, we specify the following distributed lag model:

$$\begin{aligned} \ln TFP_{it} = \gamma_0 + \sum_{s=0}^{S} \delta_s^{HR} \ln HR_{i,t-s} + \sum_{s=0}^{S} \delta_s^{CS} \ln CS_{i,t-s} \\ + \gamma_{PRU} \ln PRU_{it} + \gamma_{NRP} \ln NRP_{it} + \mu_{TFPi} + \lambda_t + \nu_{TFPit}, \end{aligned} \tag{4.11}$$

where HR_{it} is the adoption rate of 50 kg/m and over rails, CS_{it} is the adoption rate of concrete sleepers, PRU_{it} is the passengers' route-use ratio, NRP_{it} is the ratio of passengers who do not use a rail pass, μ_{TFPi} is an individual effect, λ_t is the time effect, and ν_{TFPit} is a disturbance term. Because the variables of both adoption rates include zero value observations, we add one to these variables before taking the logarithms.

Let $\theta^{HR} = \sum_{s=0}^{S} \delta_s^{HR}$, and let $\theta^{CS} = \sum_{s=0}^{S} \delta_s^{CS}$. The former, θ^{HR}, indicates the sum of the percentage increases in TFP for S years when the adoption rate of 50 kg/m and over rails increases by 1% every year. Similarly, the latter, θ^{CS}, indicates the sum of the percentage of increases in TFP for S years when the adoption rate of concrete sleepers increases by 1% every year. These are called the LRE of TFP with respect to 50 kg/m and over rails and the LRE of TFP with respect to concrete sleepers, respectively.

Figure 4.2: Changes in the Average Estimated Log of TFP of the 32 Railroad Companies in This Study



Source: Author's diagram using Annual Rail Statistics and Domestic Corporate Goods Price Index data.
Notes: The ACF (1) is the estimation assuming that companies can optimize (adjust) their labor usage in a year, depending on their productivity. The ACF (2) assumes that companies cannot optimize (adjust) their labor usage within a year, regardless of the productivity.

However, according to Wooldridge (2013), obtaining precise estimates of the LRE from equation (4.11) is often difficult because of multicollinearity: there is a substantial correlation in $\ln HR_{it}$ and $\ln CS_{it}$ at different lags. Furthermore, we cannot obtain standard errors of LRE owing to a lack of information.

To avoid these problems, we rewrite the equation. Substituting the definitions of θ^{HR} and θ^{CS} into (4.11) and rearranging, we obtain the following equivalent model (4.11):

$$\begin{aligned}\ln TFP_{it} = \gamma_0 + \theta^{HR} \ln HR_{it} + \sum_{s=1}^{S} \delta_s^{HR} \left(\ln HR_{i,t-s} - \ln HR_{it}\right) \\ + \theta^{CS} \ln CS_{it} + \sum_{s=1}^{S} \delta_s^{CS} \left(\ln CS_{i,t-s} - \ln CS_{it}\right) \\ + \gamma_{PRU} \ln PRU_{it} + \gamma_{NRP} \ln NRP_{it} + \mu_{TFPi} + \lambda_t + v_{TFPit}.\end{aligned} \tag{4.12}$$

Estimating this equation (4.12) enables us to obtain more precise estimates of each LRE and the standard errors.

Using the LSDV method, we attempted estimating (4.12) for various maximum lags, S: from zero to 17 lags. There are four possible dependent variables of (4.12): the log of TFP predicted from the OLS, LSDV, and ACF (1) and (2) estimates of the production function. However, regardless of the predicted TFP we use, the results do not change substantially. Thus, we report the estimation results using the TFP from the OLS method.

We obtain the following results about the LRE of track improvements with respect to the adoption rates of improved tracks. The coefficients of the log of the 50 kg/m and over rails ratio do not show statistical significance at any conventional significance levels, for all models, with 0–17 maximum lags. In contrast, the coefficients of the log of the concrete sleeper ratio show a positive sign and statistical significance at least 10% significance levels for models with 9–13 lags. The estimation results of the models with 8–14 maximum lags are presented in Table 4.4.

Among the results presented in Table 4.4, the model with 14 maximum lags, shown in the last column of this table, shows the highest adjusted R-squared, 0.9257. The model that shows the second highest adjusted R-squared has 11 lags and an adjusted R-squared of 0.9253. Although the coefficient of the log of the concrete sleeper ratio in the highest adjusted R-squared model with 14 lags does not show statistical significance at any conventional levels, that in the second highest adjusted R-squared model with 11 lags is 1.154 and is statistically significant at the 5% significance level. Because this coefficient represents the LRE of TFP with respect to the concrete sleeper ratio, we interpret this to mean that the TFP of a railroad company will increase by 1.554% over 11 years if the company increases the adoption rate of concrete sleepers by 1% every year, based on the model with 11 lags.

Table 4.4: Estimation Results of Distributed Lag Model with 8–14 Lags

	8 lags	9 lags	10 lags	11 lags	12 lags	13 lags	14 lags
Log of 50 kg/m and over rails ratio	−0.092	−0.174	0.080	0.462	0.750	1.162	1.499
	(0.331)	(0.344)	(0.412)	(0.556)	(0.830)	(1.121)	(1.386)
Log of concrete sleeper ratio	0.382	1.117**	1.134*	1.554**	1.589*	1.832*	1.859
	(0.672)	(0.471)	(0.644)	(0.727)	(0.860)	(1.051)	(1.467)
Log of passengers' route-use ratio	0.479**	0.687***	0.673***	0.632***	0.594***	0.651***	0.672***
	(0.222)	(0.160)	(0.162)	(0.166)	(0.184)	(0.196)	(0.164)
Log of non-rail-pass ratio	−0.112	−0.189	−0.105	0.082	0.169	0.263	0.240
	(0.236)	(0.198)	(0.182)	(0.165)	(0.305)	(0.436)	(0.442)
Constant term	−4.203***	−4.708***	−4.670***	−4.710***	−4.647***	−4.670***	−4.694***
	(0.492)	(0.385)	(0.479)	(0.506)	(0.514)	(0.580)	(0.754)
Adjusted R-squared	0.9062	0.9225	0.9220	0.9253	0.9216	0.9201	0.9257
Number of companies	39	39	39	38	37	36	36
Number of observations	432	393	354	315	277	240	204

Notes: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Company-level cluster robust standard errors are shown in parentheses. Each model includes company-level individual effects: each company's dummy variables, other than those of the first company, are included as independent variables.

4.6 Discussion

4.6.1 Simultaneity in Production Function

According to Table 4.3, the estimates of the capital, energy, and labor coefficients from ACF (1) and (2) are similar to those from the OLS method. Hence, there is a possibility that the simultaneity described in Section 4.3 is not a serious problem in this study; in other words, the simultaneity bias of the OLS estimates may not be substantial. This is probably because companies' input choices do not respond to their productivity shocks that much, owing to the difficulty of hiring or firing, no significant change in train operation schedules, slow capital accumulation, and so on.

4.6.2 Changes in TFP

The predicted log of TFP shows a declining tendency until FY 2004, and then almost stops (Figure 4.2). The change in TFP until FY 2004 is similar to that of passenger kilometers, as shown in Figure 2.1. Therefore, the decrease in TFP may have been caused by the reduction in the number of passengers. The next subsection discusses whether a decrease in TFP can be relieved by track improvements.

4.6.3 Long-run Elasticity of TFP with Respect to Track Improvements

The estimation results of the distributed lag models presented in Table 4.4 show that a 1% increase in the adoption rate of concrete sleepers every year increases (or eases the decrease in) a railroad company's TFP significantly, by about 1.1–1.8% after 9–13 years. Based on the model with the highest adjusted R-squared among those with 9–13 lags, which showed statistical significance for the coefficient of the concrete sleeper ratio, a 1% increase in the concrete sleeper ratio every year increases (or eases the decrease in) the TFP by about 1.554% after 11 years.

The reason for identifying the significant impact of increasing concrete sleepers on TFP is as follows. Replacing wooden sleepers with concrete sleepers enables railroad companies to reduce the frequency of track maintenance after, for example, 10 years (Japan Railway Construction, Transport and Technology Agency, 2008b; Board of Audit of Japan, 2016). Then, companies can carry out track maintenance using fewer trackmen. This would reduce the number of trackmen and, thus, the number of employees. In fact, the average number of construction staff (including trackmen) of the 32 railroad companies in this study decreased (Figure 4.3). Therefore, the reduction in TFP might have been eased.

In contrast, we find that an increase in the adoption rate of 50 kg/m and over rails does not affect TFP significantly. The reasons for the two different results may be that moving from wood to concrete involves installing sleepers made from quite different materials. In contrast, replacing light rails with heavier rails simply increases the mass of rails. Hence, the tolerance of a change in sleepers might be larger than that of replacing light rails with heavier rails. Therefore, the effect of installing heavy rails on maintenance frequency, number of trackmen, and TFP may be smaller than that of installing concrete sleepers on TFP.

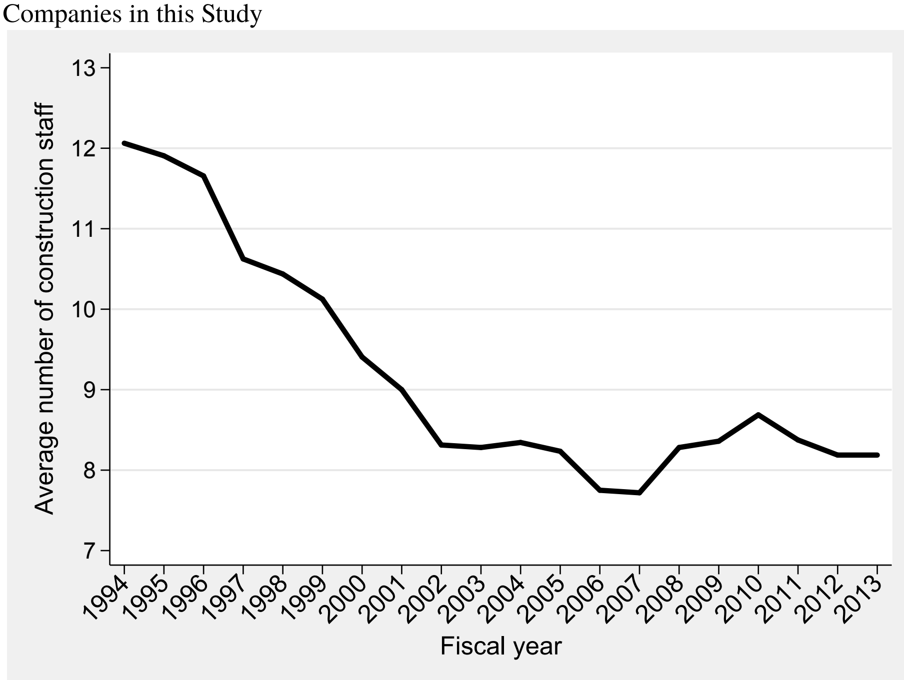
Significant results after installing concrete sleepers only become apparent after (at least) nine years, and the insignificant impact of installing heavy rails are in line with the lifespan of sleepers and rails prescribed by the ordinance. According to the Ordinance on the Life of Depreciable Assets, wooden sleepers last eight years and concrete sleepers last 20 years. In terms of rails, their lifespan is 20 years, regardless of their weight. Although railroad companies do not always replace wooden sleepers every eight years, our results are almost consistent with the ordinance, especially the period from installing concrete sleepers until its impact on TFP.

4.6.4 Robustness Check

As the maximum lag of the distributed lag model increases, the number of railroad companies in the sample decreases gradually, from 39 companies in the models with eight and nine lags model to 36 companies in the models with 13 and 14 lags (Table 4.4). This is because the data are unbalanced panel: some companies dropped from the sample during the study period. This subsection examines whether the main results are robust for the companies used in the analysis.

As mentioned previously, the models with 9–13 lags indicate the statistical significance of the coefficient of the concrete sleeper ratio. Of these, the model with 11 lags reported the highest adjusted R-squared value. The number of companies used to estimate this model is 38 (Table 4.4). Using these 38 companies, we estimate the models with nine and 10 lags again. Table 4.5 presents the results (the results of the model with 11 lags are also presented again).

Figure 4.3: Changes in the Average Number of Construction Staff of the 32 Railroad Companies in this Study



Source: Author's diagram using data from Annual Rail Statistics.

Table 4.5: Estimation Results of Distributed Lag Model for the Sample of 38 Companies

	9 lags	10 lags	11 lags
Log of 50 kg/m and over rails ratio	−0.165	0.080	0.462
	(0.343)	(0.411)	(0.556)
Log of concrete sleeper ratio	1.111**	1.134*	1.554**
	(0.470)	(0.643)	(0.727)
Log of passengers' route-use ratio	0.684***	0.673***	0.632***
	(0.159)	(0.162)	(0.166)
Log of non-rail-pass ratio	−0.196	−0.105	0.082
	(0.201)	(0.182)	(0.165)
Constant term	−4.712***	−4.670***	−4.710***
	(0.386)	(0.478)	(0.506)
Adjusted R-squared	0.9229	0.9222	0.9253
Number of observations	391	353	315

Notes: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Company-level cluster robust standard errors are shown in parentheses. Each model includes company-level individual effects: each company's dummy variables, except those of the first company, are included as independent variables. The number of companies is 38.

We obtain substantially similar results to those of the unbalanced panel. The coefficients of the log of the concrete sleeper ratio in the models with nine and 10 lags for the 38 companies in the sample are almost the same as those of the sample containing 39 companies (the unbalanced panel), as reported in Tables 4.4 and 4.5. Furthermore, their results show statistical significance at the 5% (eight lags) and 10% (nine lags) levels. The coefficients of the log of the 50 kg/m and over rails ratio are also almost the same as those of the unbalanced panel reported in Table 4.4, and neither (nine and 10 lags) of them are statistically significant. Therefore, the results are robust for the companies included in the sample.

4.7 Conclusions

This chapter investigated how long it takes for a positive effect on railroad companies' productivity to occur after improving tracks (e.g., installing heavy rails and concrete sleepers), as well as the extent of the change in productivity in the long-run. To do so, we adopt data for Japanese regional small and medium-sized railroad companies to estimate the production function, predict the TFP, and estimate distributed lag models in order to evaluate the LRE of TFP with respect to the adoption rates of heavy rails and concrete sleepers.

The empirical results indicate that a 1% increase in concrete sleepers every year may significantly increase (or relieve the reduction in) the TFP of a railroad company by about 1.554% after 11 years. However, we found no significant impact of an increase in the adoption rate of 50 kg/m and over rails on TFP. The significant positive effect of installing concrete sleepers most likely occurs because such equipment reduces the frequency of track maintenance and the number of trackmen required, although it takes a number of years before these benefits appear.

Therefore, subsidizing or promoting the adoption of concrete sleepers provides significant value. That is, subsidies can help railroad companies facing operational and investment difficulties to undertake track improvement. This may be a way to improve the long-term financial situation and the viability of Japanese small and medium-sized passenger railroad companies.

This study is not free from limitations. First, we do not clarify the considerable differences in the adoption rates of improved tracks, time taken to start upgrading rails and sleepers, or the speed of progress of track improvements among companies because these are beyond the scope of this study. In FY 2013, the *average* adoption rates were 53.9% for 50 kg/m and over rails and 51.1% for concrete sleepers (Figure 4.1). However, the adoption rates of 50 kg/m and over rails for certain companies were already 100% in FY 1994, and were still 0% for others in FY 2013. Furthermore, the FY 1994 adoption rate of concrete sleepers was more than 95%, and the FY 2013 rate remained at 0% in some cases. Future research should explore the contributory factors behind such variations, as well as companies' decisions on whether, and when, to improve their tracks. Second, we do not account for a selection bias because of the difficulty in obtaining data to do so. Because some companies dropped out of the sample during the study period, we might obtain biased estimates of the production function or the distributed lag models. To reduce the selection bias, data on the factors that affect companies' exit decisions are required. If this selection bias happens, future studies need to obtain more data and reconsider the estimation method. Third, we omitted certain companies from the sample based on the same criteria as those in Chapters 2 and 3 in order to analyze the specific types of companies throughout. Therefore, the results may not be generalizable for Japanese small and medium-sized railroad companies. Finally, the estimated coefficients of capital in the production functions were small. This is probably because we used fixed assets instead of capital stock as the capital variable. However, constructing a capital stock variable is difficult owing to a lack of data, as mentioned in Section 2.5 in Chapter 2. Because there are limitations on the estimation method, sample, and variables measurement, we need to interpret the findings carefully. Despite these limitations, we contribute by quantitatively showing that installing concrete sleepers might increase (or ease the reduction in) the TFP of railroad companies in the long-run.

Chapter 5

Conclusions

5.1 Summary of Empirical Studies

This thesis analyzed regional small and medium-sized passenger railroad companies in Japan, which are currently facing operational difficulties. By adopting panel data of these railroad companies, we estimated several empirical models based on economic theory to conduct the following examinations.

In Chapter 2, we jointly estimated the input distance function and inefficiency function to examine what type of railroad companies are technically (in)efficient. The empirical results are as follows. The railroad companies that transport mainly long-distance passengers are more technically efficient than those that transport mainly short-distance passengers. The railroad companies that transport mainly commuters are also more technically efficient than those that transport mainly non-commuters, such as tourists. The most likely reason for these results is that longer distances per boarding mean a higher value of output. In addition, railroad companies with a high ratio of rail-pass passengers transport a stable number of passengers every year.

Chapter 3 estimated the variable cost system and predicted the returns to density (RTD) of the railroad companies in order to investigate the relative size of the fixed costs of the railroad companies, as well as what type of railroad companies face high fixed costs. The findings are as follows. First, the fixed costs of the railroad companies in this study might be large. Second, the RTD of railroad companies that transport mainly non-commuting passengers (e.g., tourists) are higher than those that transport mainly commuters. Because a high RTD means high fixed costs, these results indicate that railroad companies that transport mainly non-commuters may face high fixed costs. Therefore, reducing useless facilities (e.g., rolling stocks or tracks) would improve these companies' performance and their long-run viability, especially in the case of companies that transport mainly non-commuters.

In Chapter 4, we examined how long it takes to increase (or ease decrease in) the productivity of railroad companies after track improvements, such as installing heavy rails and concrete sleepers, and by how much such track improvements increase (or ease the decrease in) the productivity in the long run. Here, we estimated a production function, predicted the total factor productivity (TFP) of the railroad companies, and estimated distributed lag models in order to evaluate the long-run elasticity (LRE) of TFP with respect to the adoption rates of heavy rails and concrete sleepers. The empirical results indicate that a 1% increase in concrete sleepers every year may increase (or ease the reduction in) the TFP of railroad company by about 1.554% after 11 years, while installing 50 kg/m and over rails may not positively affect TFP. We found a significant positive effect of installing concrete sleepers because such equipment reduces not only the frequency of track maintenance, but also the number of trackmen required. Thus, subsidizing or promoting the replacement of wooden sleepers with concrete sleepers would improve Japanese small and medium-sized passenger railroad companies' long-term performance and viability.

In summary, first, Japanese regional small and medium-sized passenger railroad companies that transport mainly short distance passengers and those that transport mainly non-commuters operate inefficiently. Second, railroad companies that transport mainly non-commuters may face operational difficulties owing to high fixed costs. Third, railroad companies can remove useless tracks or rolling stocks and install concrete sleepers in order to improve their performance and long-period viability. Finally, governments should continue subsidizing railroad companies' installations of concrete sleepers. Thus, the objectives of this thesis addressed in Section 1.2 are achieved.

5.2 Limitations and Future Research

The limitations common to Chapters 2, 3, and 4 are the omission of certain types of railroad companies from the sample and the definition of the capital variable.

As mentioned in these chapters, we omitted railroad companies such as those that use diesel vehicles and third-sector railroad companies, which operate *heiko zairaisen* routes that run on high-speed lines and that were operated by private companies before the high-speed lines opened. Third-sector companies in Japan are those with both private and public stakeholders. As explained in sections 2.5 and 3.5, the construction of energy or energy price variables is difficult if there are multiple types of energy in the sample. We can convert oil consumption to electricity consumption (Mizutani and Uranishi, 2007; Mizutani et al., 2009). However, when we tried doing so, including companies using diesel and the *heiko zairaisen* third-sector railroad companies in the sample, and estimated the variable cost function in Chapter 3, we obtained a positive coefficient of the capital variable in the variable cost function and a variable cost function that is not concave with respect to input prices. Thus, we omitted these companies in our analyses in Chapters 2 and 4, as well as in Chapter 3 in order to analyze the specific types of companies throughout. Therefore, the results may not be generalizable for Japanese regional small and medium-sized passenger railroad companies. Nevertheless, we attempted to increase the generality by controlling for each company's time-invariant heterogeneity. Here, we included each company's individual fixed effect in the input distance function (Chapter 2), variable cost function (Chapter 3), and distributed lag model (Chapter 4).

Defining the capital variable as a tangible fixed asset is another limitation of this study. We obtained quite small coefficients of capital for the input distance function (Chapter 2) and the production function (Chapter 4). Furthermore, the cost function estimated in Chapter 3 did not satisfy the monotonicity condition with respect to capital for some observations. The reason for these results is probably that we used fixed asset data. As mentioned in Section 2.5, some studies, such as Bogart and Chaudhary (2013), define capital as capital stock, estimated using the perpetual inventory method. Although estimating capital stock requires equipment investment data, these are unavailable for railroad companies in Japan. When we attempted to estimate the railroad companies' investments using the method proposed by Tanaka (2010), we could not obtained good estimates: some companies' nominal gross investment were negative. As another approach, we could use a flow variable as capital (Harada, 2016). However, few studies have defined capital as a flow variable.

Future research should reconsider the functional form of the distance, cost, and production functions in order to obtain estimates that are more consistent with economic theory and that are more generalizable for Japanese regional small and medium-sized passenger railroad companies. Furthermore, future research should reconsider the definition of the capital variable of the functions, and perhaps try using a flow variable as capital. If capital stock data on railroad companies in Japan become available, we may be able to estimate the functions more precisely, which would lead to better implications.

Appendix A

Deriving Formula of Returns to Density

Suppose that a railroad company supplying passenger-transportation services uses variable inputs (energy, labor, and material) and fixed input (capital), similar to the empirical analysis in chapter 3. The company's short-run variable cost function is written as the sum of expenditure on variable inputs:

$$\begin{aligned} g(\ln x_E, \ln x_L, \ln x_M) &= w_E \exp(\ln x_E) + w_L \exp(\ln x_L) + w_M \exp(\ln x_M) \\ &= w_E x_E + w_L x_L + w_M x_M, \end{aligned} \tag{A.1}$$

where w_E is energy price, w_L is wage, w_M is material price, x_E is energy consumption, x_L is the number of employees, and x_M is material usage. For simplicity's sake, the subscripts of i (company) and t (year) are omitted. The transformation function for the structure of production is

$$F(\ln \psi, \ln x_E, \ln x_L, \ln x_M, \ln k, t) = 1, \tag{A.2}$$

where ψ is output, k is capital, and t is year. In the short-run, the company minimizes its variable cost, at a given level of output (transport volume), input prices, and fixed input (capital). The company's cost minimization problem is written as follows:

$$\min_{\ln x_E, \ln x_L, \ln x_M} \ln g(\ln x_E, \ln x_L, \ln x_M), \tag{A.3}$$

$$\text{s.t. } F(\ln \psi, \ln x_E, \ln x_L, \ln x_M, \ln k, t) = 1. \tag{A.4}$$

Lagrange function is

$$L = \ln g(\ln x_E, \ln x_L, \ln x_M) + \lambda[F(\ln \psi, \ln x_E, \ln x_L, \ln x_M, t) - 1]. \tag{A.5}$$

First order conditions are

$$\frac{\partial L}{\partial \ln x_E} = 0 \Leftrightarrow \frac{\partial \ln g}{\partial \ln x_E} = -\lambda \frac{\partial F}{\partial \ln x_E} \Leftrightarrow -\frac{1}{\lambda}\frac{\partial \ln g}{\partial \ln x_E} = \frac{\partial F}{\partial \ln x_E}, \tag{A.6}$$

$$\frac{\partial L}{\partial \ln x_L} = 0 \Leftrightarrow \frac{\partial \ln g}{\partial \ln x_L} = -\lambda \frac{\partial F}{\partial \ln x_L} \Leftrightarrow -\frac{1}{\lambda}\frac{\partial \ln g}{\partial \ln x_L} = \frac{\partial F}{\partial \ln x_L}, \tag{A.7}$$

$$\frac{\partial L}{\partial \ln x_M} = 0 \Leftrightarrow \frac{\partial \ln g}{\partial \ln x_M} = -\lambda \frac{\partial F}{\partial \ln x_M} \Leftrightarrow -\frac{1}{\lambda}\frac{\partial \ln g}{\partial \ln x_M} = \frac{\partial F}{\partial \ln x_M}, \tag{A.8}$$

$$\frac{\partial L}{\partial \lambda} = 0 \Leftrightarrow F(\ln \psi, \ln x_E, \ln x_L, \ln x_M, t) - 1 = 0. \tag{A.9}$$

From these conditions, we obtain the solution for the cost minimization problem, $(\ln \hat{x}_E, \ln \hat{x}_L, \ln \hat{x}_M)'$. This is the function of $\ln \psi$, $\ln \boldsymbol{w}'$, and $\ln k$, where $\boldsymbol{w}' = (w_E, w_L, w_M)'$.

Subsequently, consider the total differential of the transformation function (A.2):

$$\begin{aligned} &\frac{\partial F}{\partial \ln \psi} d \ln \psi + \frac{\partial F}{\partial \ln x_E} d \ln x_E + \frac{\partial F}{\partial \ln x_L} d \ln x_L \\ &+ \frac{\partial F}{\partial \ln x_M} d \ln x_M + \frac{\partial F}{\partial \ln k} d \ln k + \frac{\partial F}{\partial t} dt = 0. \end{aligned} \tag{A.10}$$

Returns to density (RTD) is defined as the proportional increase in output caused by a proportional increase in all the inputs with network size (and time) held fixed (Caves et al., 1985; Smith et al., 2015): $d \ln x_E = d \ln x_L = d \ln x_M = d \ln k \equiv d \ln x$, $dt = 0$. Substituting these into the total differential (A.10), we can express RTD as follows:

$$\text{RTD} = \frac{d \ln \psi}{d \ln x} = -\frac{\partial F/\partial \ln x_E + \partial F/\partial \ln x_L + \partial F/\partial \ln x_M + \partial F/\partial \ln k}{\partial F/\partial \ln \psi}. \tag{A.11}$$

Subsequently, we substitute the solution of the cost minimization problem into the variable cost function (A.1) and define

$$\begin{aligned}&\ln c(\ln \psi, \ln \boldsymbol{w}', \ln k)\\&\quad = \ln g\left(\ln \hat{x}_E(\ln \psi, \ln \boldsymbol{w}', \ln k), \ln \hat{x}_L(\ln \psi, \ln \boldsymbol{w}', \ln k), \ln \hat{x}_M(\ln \psi, \ln \boldsymbol{w}', \ln k)\right).\end{aligned} \tag{A.12}$$

Partial derivatives of (A.12) with respect to $\ln \psi$ and $\ln k$ are

$$\frac{\partial \ln c}{\partial \ln \psi} = \frac{\partial \ln g}{\partial \ln x_E}\frac{\partial \ln \hat{x}_E}{\partial \ln \psi} + \frac{\partial \ln g}{\partial \ln x_L}\frac{\partial \ln \hat{x}_L}{\partial \ln \psi} + \frac{\partial \ln g}{\partial \ln x_M}\frac{\partial \ln \hat{x}_M}{\partial \ln \psi}, \tag{A.13}$$

$$\frac{\partial \ln c}{\partial \ln k} = \frac{\partial \ln g}{\partial \ln x_E}\frac{\partial \ln \hat{x}_E}{\partial \ln k} + \frac{\partial \ln g}{\partial \ln x_L}\frac{\partial \ln \hat{x}_L}{\partial \ln k} + \frac{\partial \ln g}{\partial \ln x_M}\frac{\partial \ln \hat{x}_M}{\partial \ln k}, \tag{A.14}$$

respectively. Furthermore, we substitute the solution of the cost minimization problem into the transformation function (A.2):

$$\begin{aligned}&F\left(\ln \psi, \ln \hat{x}_E(\ln \psi, \ln \boldsymbol{w}', \ln k), \ln \hat{x}_L(\ln \psi, \ln \boldsymbol{w}', \ln k), \ln \hat{x}_M(\ln \psi, \ln \boldsymbol{w}', \ln k), \ln k, t\right)\\&= 1.\end{aligned} \tag{A.15}$$

This function is true for all the values of $\ln \psi$, $\ln \boldsymbol{w}$, and $\ln k$. Partial derivatives of both sides of (A.15) with respect to $\ln \psi$ and $\ln k$ are

$$\begin{aligned}&\frac{\partial F}{\partial \ln \psi} + \frac{\partial F}{\partial \ln x_E}\frac{\partial \ln \hat{x}_E}{\partial \ln \psi} + \frac{\partial F}{\partial \ln x_L}\frac{\partial \ln \hat{x}_L}{\partial \ln \psi} + \frac{\partial F}{\partial \ln x_M}\frac{\partial \ln \hat{x}_M}{\partial \ln \psi} = 0\\&\qquad \Leftrightarrow \frac{\partial F}{\partial \ln x_E}\frac{\partial \ln \hat{x}_E}{\partial \ln \psi} + \frac{\partial F}{\partial \ln x_L}\frac{\partial \ln \hat{x}_L}{\partial \ln \psi} + \frac{\partial F}{\partial \ln x_M}\frac{\partial \ln \hat{x}_M}{\partial \ln \psi} = -\frac{\partial F}{\partial \ln \psi},\end{aligned} \tag{A.16}$$

$$\begin{aligned}&\frac{\partial F}{\partial \ln x_E}\frac{\partial \ln \hat{x}_E}{\partial \ln k} + \frac{\partial F}{\partial \ln x_L}\frac{\partial \ln \hat{x}_L}{\partial \ln k} + \frac{\partial F}{\partial \ln x_M}\frac{\partial \ln \hat{x}_M}{\partial \ln k} + \frac{\partial F}{\partial \ln k} = 0\\&\qquad \Leftrightarrow \frac{\partial F}{\partial \ln x_E}\frac{\partial \ln \hat{x}_E}{\partial \ln k} + \frac{\partial F}{\partial \ln x_L}\frac{\partial \ln \hat{x}_L}{\partial \ln k} + \frac{\partial F}{\partial \ln x_M}\frac{\partial \ln \hat{x}_M}{\partial \ln k} = -\frac{\partial F}{\partial \ln k},\end{aligned} \tag{A.17}$$

respectively. Substituting (A.6), (A.7), (A.8), (A.16), and (A.17) into (A.13) and (A.14), we obtain

$$
\begin{aligned}
\frac{\partial \ln c}{\partial \ln \psi} &= -\lambda \frac{\partial F}{\partial \ln x_E} \frac{\partial \ln \hat{x}_E}{\partial \ln \psi} - \lambda \frac{\partial F}{\partial \ln x_L} \frac{\partial \ln \hat{x}_L}{\partial \ln \psi} - \lambda \frac{\partial F}{\partial \ln x_M} \frac{\partial \ln \hat{x}_M}{\partial \ln \psi} \\
&= -\lambda \left(\frac{\partial F}{\partial \ln x_E} \frac{\partial \ln \hat{x}_E}{\partial \ln \psi} + \frac{\partial F}{\partial \ln x_L} \frac{\partial \ln \hat{x}_L}{\partial \ln \psi} + \frac{\partial F}{\partial \ln x_M} \frac{\partial \ln \hat{x}_M}{\partial \ln \psi} \right) \\
&= -\lambda \cdot \left(-\frac{\partial F}{\partial \ln \psi} \right) \\
&= \lambda \frac{\partial F}{\partial \ln \psi} \\
\Leftrightarrow \frac{1}{\lambda} \frac{\partial \ln c}{\partial \ln \psi} &= \frac{\partial F}{\partial \ln \psi}, \qquad \text{(A.18)} \\
\frac{\partial \ln c}{\partial \ln k} &= -\lambda \frac{\partial F}{\partial \ln x_E} \frac{\partial \ln \hat{x}_E}{\partial \ln k} - \lambda \frac{\partial F}{\partial \ln x_L} \frac{\partial \ln \hat{x}_L}{\partial \ln k} - \lambda \frac{\partial F}{\partial \ln x_M} \frac{\partial \ln \hat{x}_M}{\partial \ln k} \\
&= -\lambda \left(\frac{\partial F}{\partial \ln x_E} \frac{\partial \ln \hat{x}_E}{\partial \ln k} + \frac{\partial F}{\partial \ln x_L} \frac{\partial \ln \hat{x}_L}{\partial \ln k} + \frac{\partial F}{\partial \ln x_M} \frac{\partial \ln \hat{x}_M}{\partial \ln k} \right) \\
&= -\lambda \cdot \left(-\frac{\partial F}{\partial \ln k} \right) \\
&= \lambda \frac{\partial F}{\partial \ln k} \\
\Leftrightarrow \frac{1}{\lambda} \frac{\partial \ln c}{\partial \ln k} &= \frac{\partial F}{\partial \ln k}. \qquad \text{(A.19)}
\end{aligned}
$$

Totaling both the sides of (A.6), (A.7), and (A.8) gives

$$\begin{aligned}
\frac{\partial F}{\partial \ln x_E} + \frac{\partial F}{\partial \ln x_L} + \frac{\partial F}{\partial \ln x_M} &= -\frac{1}{\lambda}\frac{\partial \ln g}{\partial \ln x_E} - \frac{1}{\lambda}\frac{\partial \ln g}{\partial \ln x_L} - \frac{1}{\lambda}\frac{\partial \ln g}{\partial \ln x_M} \\
&= -\frac{1}{\lambda}\left(\frac{\partial \ln g}{\partial \ln x_E} + \frac{\partial \ln g}{\partial \ln x_L} + \frac{\partial \ln g}{\partial \ln x_M}\right) \\
&= -\frac{1}{\lambda}\left(\frac{x_E}{g}\frac{\partial g}{\partial x_E} + \frac{x_L}{g}\frac{\partial g}{\partial x_L} + \frac{x_M}{g}\frac{\partial g}{\partial x_M}\right) \\
&= -\frac{1}{\lambda}\left(\frac{x_E}{g}w_E + \frac{x_L}{g}w_L + \frac{x_M}{g}w_M\right) \\
&= -\frac{1}{\lambda}\cdot\frac{w_E x_E + w_L x_L + w_M x_M}{g} \\
&= -\frac{1}{\lambda}\cdot\frac{g}{g} \\
&= -\frac{1}{\lambda}. \qquad \text{(A.20)}
\end{aligned}$$

The fourth equal sign comes from (A.1).

Substituting (A.18), (A.19), and (A.20) into (A.11), we obtain

$$\mathrm{RTD} = -\frac{(-1/\lambda) + (1/\lambda)\cdot \partial \ln c/\partial \ln k}{(1/\lambda)\cdot \partial \ln c/\partial \ln \psi} = \frac{1 - \partial \ln c/\partial \ln k}{\partial \ln c/\partial \ln \psi}. \qquad \text{(A.21)}$$

See Caves et al. (1981) for an explanation on the derivation of this formula.

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